5. Are climbers fools? Modeling risky recreation

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1. INTRODUCTION

In this chapter we examine the recreational activity known as rock climbing, linking this activity to the economics of risk-taking. Nearly all economic studies of risk or uncertainty relate to financial risk and/or portfolio management. Recently, however, people engaged in the valuation of environmental amenities have recognized the need to allow their models to incorporate an individual's uncertainty about the environment or some decision that must be made and, at times, complex behaviors under risky conditions. Still, the vast majority of recreation studies have assumed no uncertainty or risk while explaining recreationists' behavior, even those that do examine recreational activities one might deem risky. For example, nearly all of the analyses of rock climbing apply the standard random utility or count data versions of the travel cost model of recreation demand, with none of them involving aspects of risk except in a very minor way (Ekstrand, 1994; Shaw and Jakus, 1996; Grijalva et al., 2002a, 2002b; Hanley et al., 2001; and Hanley et al., 2002).

Nearly all of these rock climbing studies examine access to climbing areas in the United States or Scotland, focusing on where participants go climbing and how often. These studies have been motivated by proposed climbing management plans that may restrict climbing access on public land used by climbers. In recent years managers of public lands have grown concerned that rock climbing harms resources or have become aware of potential conflicts between rock climbers and other types of public lands users.1 The 'certainty' models used in previous studies typically explain how an individual's destination, trip-making frequency, or total seasonal participation may change under the new regulatory policies. Conventional welfare measures under certainty are derived to examine the losses or gains of some access restrictions. For example, Grijalva et al. (2002a and 2002b) examine the losses to climbers who visit Hueco Tanks near El Paso Texas and, more broadly, the losses to climbers for access restrictions in wilderness areas at a host of climbing areas around the United States.

Many researchers have attempted to lay out a framework for participation in risky recreation such as rock climbing or similar pursuits such as mountaineering, scuba diving, canoeing or white-water rafting, and big-game hunting, but most of this research focuses on why individuals become attracted to risky forms of leisure in the first place (for example, Slanger and Rudestam, 1997; Schreyer and White, 1979; Robinson, 1992). The perception of risk by participants in risky activities has been studied by Chonon and Ritchie (1982). Jakus and Shaw (1996) explored trade-offs between technical difficulty and risk ratings communicated for particular climbing routes.

Risky recreation is clearly being undertaken by an increasingly large number of participants around the world; to the degree that risk attributes of the sport affect the choice of destination and trip frequency decisions, economists may need to develop models that incorporate this attribute of the behavioral decision process.2 Our specific goal in this chapter is to consider whether it makes a difference if we model the demand for recreation with explicit recognition of the risk, as opposed to modeling the demand for climbing ignoring risks. The standard approach to modeling demand for recreation assumes that the individual has 'perfect' information regarding all choices, and that she or he is certain about outcomes. Climbers, in contrast, face many risks, including the risk of injury or death, the risk of not completing a route, and risks associated with weather and crowds. We show how a consideration of risk results in demand models that differ from the usual model of recreation activities. Our discussion is presented within the context of risks associated with injury or death because these are probably the most interesting and important aspects for both climbers and economists. While some authors have considered some type of uncertainty and risk in recreation, none have considered risk of injury, and none that we know of have used revealed preference data in the empirical modeling.3

Although rock climbing is the risky recreation examined in this chapter, our results can be generally applied to several other forms of recreation that involve risks. The economic model focuses not on the individual's motives to take up the sport in the first place, but on the determinants of the destinations, frequency of visits, and the willingness to incur risk. A parallel with other risky recreational pursuits can be found in the way that climbers sometimes refer to success as 'bagging' a route, which conjures up the hunter's claim of 'bagging' a deer or elk. Both involve uncertainty, with no guarantee of success.

The remainder of the chapter begins with details on the sport of rock climbing (Section 2). In Section 3 we present some preliminary empirical
results that are relevant to modeling and understanding risky recreation. The information presented in Section 3 is used to motivate the risk-related travel cost demand models presented in Section 4. We do not actually estimate the parameters of a risky recreation demand model in this chapter because the data necessary to do so are not available to us at this time. Our focus, instead, is on the implications of risk for future welfare analysis. Section 5 summarizes the chapter and offers some suggestions for future research in this area.

2. THE RISKY GAMES CLIMBERS PLAY

We begin this section with a description of the activity of rock climbing, so that the models proposed in Section 4 can be better understood. Though several scholarly papers on rock-climbing have been published, none completely explain what goes on in the sport, nor do they differentiate between the varieties of climbing (and risk) that can be experienced in a variety of settings and configurations of rock.

Technical rock climbing on smaller cliffs or ‘crags’ involves the choice of specific routes up the rockface. Routes differ in their degree of difficulty, length and other aesthetic aspects, as well as the degree of risk involved. Technical climbing usually involves the use of ropes and climbing gear to protect the climber in the event of a fall. The equipment used to protect the climber from hitting the ground or rock feature after falling varies from hardware (metal devices) placed permanently in the rock (a bolt or piton), to metal devices that can be temporarily inserted into cracks and fissures, and later removed. Using either one, as the ‘leader’ climbs, the rope is run through these devices, one of which will act as a fulcrum point in the event of a fall. The second climber (or ‘second’) holds (belay) the rope from the bottom. The leader advances using the features of the rock, with the climbing equipment used to protect against the consequences of a fall which would otherwise result in injury. After belaying the leader, the second advances up, also using rock features, but he or she is quite well protected by the rope above, and thus takes little or no risk of injury.

Specific climbs or ‘routes’ are often rated according to technical or gymnastic difficulty and also for their assessed risk. Technical ratings are initially proposed by the first ascent party but, as the route is climbed by others over the years, a consensus rating is determined. Such consensus ratings are published in readily available climbing guidebooks (for popular areas) or spread by word of mouth (for less popular areas). These are much like fishing guides or trail or hiking guides. Guidebooks note the location and length of a route, its technical difficulty, a quality rating, and whether the climb can be well protected or not (the risk scale). In the United States, the risk ratings were developed in the 1970s, and were based on the letters used by the Motion Picture Association to designate suitability of a film for different viewers: G, PG, R, and X. Specific climbs or routes that the leader can protect safely are rated ‘G’ (excellent protection) or ‘PG’ (good protection). Rock climbs that cannot be well protected are typically rated with an ‘R’ or, when protection is extremely poor to non-existent, an ‘X’. An R-rating indicates that should the climber fall, even with the use of protective equipment, the fall would likely result in serious injury. This is because the places in the rock for protection will likely cause the climber to climb long distances between protection points; if a fall occurs it will be a long one, which may heighten the probability of hitting the rock or the ground. An X-rating indicates protection possibilities that are so poor that, should the climber fall, death would be a near certainty. Other than this, little is communicated about risks in rock climbing on a widespread basis, at least in terms of information that climbers can readily access. Based on our experience, we know that climbers often share details with others about routes they have done, and this information is passed along in the community, most often by word-of-mouth.

Given the information available about climbing routes, climbers may choose from a variety of potential outdoor climbing experiences. One climber may push her athletic limit by choosing a well-protected climb with a technical difficulty at or beyond her current technical limit. This climber may fall frequently, but safely, in her attempts. Another climber may play a more psychological game by choosing to lead an R- or X-rated climb, perhaps technically easier, but one which requires ‘mind control’ to complete the risky route. This climber would not wish to fall, since it would result in injury. Others may choose an ‘easy’ day at the crag, climbing only safe routes well within their technical ability, or maximizing the vertical distance or number of vertical feet successfully climbed. Finally, some may choose to minimize risk altogether by always choosing to climb with a rope from above. These activities are clearly in contrast to the assumption by some researchers that the sole goal in climbing is to ‘get to the top’ by any means necessary. Whereas this may be a reasonable assumption to make in considering the sport of mountain climbing or mountaineering, it is often inappropriate for rock climbing.

3. SOME RELEVANT PRELIMINARY EMPIRICAL RESULTS

In this section we present some preliminary empirical results relevant to modeling and understanding risky recreation. The data come from a Fall
1993 mail survey of members of the Mohonk Preserve in New York State and were used by Shaw and Jakus in their studies. We use these data to guide us in identifying which risk-related aspects of rock climbing behavior are important to climbers and, thus, important to those wishing to model such behavior.

The Mohonk Preserve offers some of the finest rock climbing in the United States and is visited by climbers from all over the world. Compared to other nationally-known climbing areas, the Preserve is somewhat unusual in that it maintains a policy of not allowing new bolts or pitons to be placed in the cliffs. Climbers must use their own protection, or the few existing permanent protection (bolts and pitons) that had been permitted in the past. Of the 892 respondents to the Mohonk Preserve survey, 221 stated that they took a climbing trip in 1993. The group who returned the survey is well educated and has a high average household income.

### 3.1 The Primary 'Goal' of Rock Climbers

Casual perusal of the Mohonk Preserve climbing guidebooks dissuades researchers of the notion that reaching the top of these routes is the most important goal. The area's guidebooks report the full description of a route followed, for example, by a statement that 'most people only climb the first rope-length'. This occurs because this section of the route contains the best (or hardest) quality climbing, with the remainder of the route being unpleasant or too easy. Results from the Mohonk Preserve sample of rock climbers also illustrate that 'getting to the top' is not a consideration for nearly half the respondents, and that route difficulty is sought out, not avoided. First, a majority of climbers (60 per cent) most frequently choose to do routes that are just at or above, not below the grade at which they are technically able to climb without falling. In addition, when asked how they 'normally' finished a climb, 51 per cent said they continue to the top, 11 per cent said they rappelled (descended on the rope) after one or more rope-lengths of climbing, and 38 per cent had no preference. Thus, fully half of our responding sample of climbers defined success as something other than completing the route. Respondents were also asked to rate the attractions of a trip to the Preserve on a 1 (most important) to 5 (least important) scale. A large number of climbers gave 'physical challenge' a score of 1 (60 per cent of those who responded). This supports earlier evidence (for example, Ewert, 1985) that the challenge is important to this group of individuals. These data suggest that an expected utility model based on the risky outcome of 'getting to the top' would be misdirected, at least for rock climbers.

### 3.2 Risk Attitudes, Risk-taking Behavior and the Probability of Failure

Climbers in the Preserve study were asked whether the Preserve's policy of no bolting should be maintained, or reconsidered. Recall that bolts very likely reduce the risks of injury or death, so one might assume climbers would be in favor of reconsidering this policy. Of those responding to the question, 68 per cent said it should be maintained. Only 1 per cent thought the policy should be revoked, while 31 per cent said it should be reconsidered, with the majority of these saying it should be reconsidered to increase safety. We learn several things here. First, there are ways of climbing safely without bolts, and a majority of Preserve climbers do not mind these alternatives. Second, attitudes toward bolting do not necessarily reveal a preference for taking risks because climbs with poor protection may be avoided. More careful questions have to be asked of the climbers to further explore this issue of bolting and how it relates to risk-taking and the experience.

The Mohonk questionnaire also asked climbers to describe a typical day at the Preserve. Of those who responded, only 7 per cent always climb on a toprope, which involves little or no risk because the rope is always above the climber to protect him. An additional 18 per cent said they usually toprope a specific route, with the remaining 75 per cent climbing with a toprope only infrequently. This shows that few climbers approach their sport in a manner in which they can always minimize risk.

Climbers were also asked whether they led climbs that were rated 'R' (serious injury if a fall is taken) or 'X' (death in the event of a fall) (see Jakus and Shaw, 1996). The responses clearly indicate that many climbers voluntarily assume risk of injury or death. Of those who answered, 31 per cent said they led R-rated climbs and 20 per cent said they led X-rated climbs, or climbed without a rope. The questionnaire also asked the level of difficulty at which the climber said he led the R or X climb. The risk in these endeavors, whether real or perceived, may decline if the climber leads a route that protects poorly, but is well below his or her level of ability. Of those who said they led R-rated climbs, 30 per cent said they lead the same level of technical difficulty as they would for a G- or PG-rated climb. Fifty-one per cent said they lead one level lower than they report leading normally, and 11 per cent said they lead two levels lower. A similar comparison for leaders of X-rated climbs found that only 10 per cent said they lead at the same level of technical difficulty as a G- or PG-rated climb, 41 per cent said one level lower, and 39 per cent said two levels lower.

We note that the number who lead at the same level as their ability drops significantly when the outcome from the fall increases from injury (R) to death (X). This finding is consistent with two key aspects of behavior. First, climbers appear to avoid risk and second, the probabilities of failure are
controlled to a degree by the climber (see Jakus and Shaw, 1996). Climbers are adjusting the difficulty downward when climbing an R- or X-rated route to decrease the probability of injury. Again, this behavior suggests the conventional expected utility model, which assumes exogenous risk probabilities, may be inappropriate unless ability and difficulty can be integrated with the probability of injury. It is also interesting to examine those individuals who lead R- and X-rated climbs and their responses on the questions pertaining to the bolting policy. We might expect that, if the thrill of the potential injury or death motivates them in choosing climbing routes, this group may be against any new bolts or pitons. However, for the 81 individuals who lead either R- or X-rated climbs, 40 per cent thought the policy should be reconsidered and 19 per cent of this group said so because of safety reasons.

3.3 Summary: Key Features of Climbers' Behavior to be Modeled

The behavioral data indicate the ways in which the empirical recreational demand model should be extended. First, consider the notion that an important risky attribute of climbing is the uncertainty associated with reaching the top of the cliff. This is unfounded. Climbers often seek out routes of extreme difficulty that many falls are expected; recall that falling without injury is common. Further, climbers may focus on successfully completing only a portion of a route, choosing to return to the ground after completing this section. Second, ‘falling’ is part of the game because physical challenge is an important element of the sport. Third, the key risk that remains is the risk of injury or death. Climbers appear to recognize this as an integral element of the sport, but one that can be controlled to some degree through judicious selection of climbing routes. Thus, the risk of injury or death may, in some large part, be endogenous to the climber, at least in an *ex ante* sense. These facts guide us in model development.

4. THE MODELS

4.1 Demand under Certainty

A wide variety of certainty-based (no risk) recreation demand models use the theory of consumer behavior and observed trip data to explain the choice of destinations and/or the number of trips to particular recreation areas. Typical models use the individual’s travel costs to and from a recreation destination to proxy the market price of the good, and are thus often referred to as travel cost models (TCM). These are also called *revealed preference* models because they reveal the value of non-market resources (a site or site attribute) through actual behavior. These models allow the value, or maximum willingness to pay (WTP), for access to the recreation site(s) or the value of changes in site quality to be estimated. Modern methods allow estimation of the compensating (CV) or equivalent variation (EV) measures of consumers' surplus.

CV or EV are often used in the analysis of different policy scenarios. We assume the reader is familiar with this literature and do not make any attempt to comprehensively reference what must be hundreds of recreation demand studies. Recent advances in computing, econometric theory, and readily-available software, however, has led to widespread use of the random utility model (RUM) or count data models (the Poisson, negative binomial, and its variants) in travel cost modeling. Each of these techniques was adopted simply because the standard unit of consumption is a recreation ‘trip’ and a trip is a discrete random variable. As noted in the first chapter of this volume, recent concerns about correlation patterns have caused researchers to consider even more sophisticated econometric modeling approaches (random parameters logit, and so on).

The large strides made in the econometrics of travel cost modeling may not have been matched by corresponding developments in the microeconomic theory that underlies it. Few researchers seem willing to tackle difficult theoretical issues in travel cost modeling such as dealing with trips of different lengths, connections between the trips over a longer period of choice, the role that time plays in the choice of activities, and uncertainty or risks. We make no suggestion that these issues are trivial – they are very, very difficult aspects relating to behavior.

Despite the implication of its name, the ‘random’ part of the conventional RUM approach does not imply any sort of gamble on the part of individuals. When the individual makes a decision he weighs the utility he gets from recreating at site *j* against the utility he gets from visiting any other alternative site *k*: if utility is greatest at site *j* relative to all other sites *k* on some choice occasion, he goes to site *j*. Utility is random only from the researcher’s perspective. The RUM-based WTP is the maximum amount of money the recreational user expects to pay to experience recreation at a site, knowing all conditions relating to whether he may or may not go to the site, or how many trips will be taken there. As will be demonstrated below, this is different from the WTP measure stemming from a model with uncertain outcomes or site conditions.

4.2 Demand under Uncertainty: Review

The derivation of the demand for goods and services in the presence of risk still owes much to the expected utility model (EUM) originally proposed
by Bernoulli in 1738 and advanced by von Neumann and Morgenstern in 1947. To provide some intuition, we will apply this framework to a risky climbing situation. Let utility \( U \) for the individual (suppressing an indicator for individual \( i \)) be a function of some non-stochastic variables in a vector of goods \( G \) (including recreation trips), exogenous attributes of the climbing route or area \( q \), and a function of being healthy (state \( H, H = 1 \)), or injured or dead (state \( I, H = 0 \)). The attributes \( q \) could include route length, quality of the climbing, and the injury incurred in the event of a fall (that is, the \( R \)- or \( X \)-rating). Assume, for the moment, that both states are such that the probabilities of state-dependent utilities can be accurately assessed by experts and are thus exogenous to the individual. Utility when healthy is given by \( U_H = U_H(G, q, H = 1) \), and when injured it is \( U_I = U_I(G, q, H = 0) \), and the probability of each state is \( \pi \), and \( 1 - \pi \) respectively. Then expected utility in this simple two-state world is:

\[
EU = \pi U_H(G, q, H = 1) + (1 - \pi) U_I(G, q, H = 0) \quad (5.1)
\]

Assuming the axioms of the expected utility model are satisfied one can maximize EU subject to the usual budget \( (m) \) constraint (see Starmer, 2000). The solution to the expected utility problem leads to expected demands for \( G \) from which welfare measures can be derived.

One of the often discussed welfare measures is the expected surplus, ES, which is simply the probability-weighted ex post consumers' surpluses summed together. Using the above, if one knew that consumers' surplus from some change when definitively injured was \( CS_I \) and when healthy was \( CS_H \), then \( ES = \pi CS_H + (1 - \pi) CS_I \). As an example, consider what ex post ES tells us as researchers. Suppose a climber attempts a route with quality attributes \( q_0 \) and the climber stays healthy, which happens with a probability \( \pi = 0.75 \). If \( CS_H = \$15 \) and \( CS_I = \$10 \), then the probability-weighted sum of the ex post surpluses is \$13.75, also known as the expected surplus (ES). If there were more than two outcomes (each with known probability), we would simply add these in the determination of ES over all outcomes.

The problem is that ex post surplus calculations imply a resolution to the uncertainty and, thus, the measure is of limited use in practice. For the decision involving, say, whether to attempt a risky climbing route, the choice must be made ex ante, and welfare measures involving this uncertainty should reflect this aspect of the choice. The option price (OP) has been found to be the most desirable welfare measure under uncertainty because it incorporates the idea that an ex ante payment could be made prior to the resolution of the uncertainty. The OP is most often defined for a price change, where the price faced by the consumer is uncertain. Graham (1981) defines OP in the context of collective risk and provision of a public good (a dam), where risk is associated with uncertain weather (dry or wet). Within the context of risky recreation, such a collective good could be rescue services \( (RS) \) in the event of an injury or bolt replacement for aging climbing anchors. For the purposes of the following exposition, let OP be the ex ante payment needed to assure that rescue services are available \( (RS = 1) \).

Injury may take various forms of severity; let the health status of the individual be described by some random variable \( H \), where \( H \) is a function of climbing route and climber-specific attributes. In particular, let health status be a random variable and a function of three route attributes, the technical difficulty rating, \( D \), the hazard warning \( R \) or \( X \), and a climber's ability, \( A \), so that for an \( R \)-rated route the function is,

\[
H = H(D, R, A) \quad (5.2)
\]

noting that this can also take on a distribution. We might in fact add an error term denoting the 'random' aspects of the climbing experience that can influence deterministic health status, but this is not necessary to introduce uncertainty. For example, a climber may be injured by rockfall, the route may have loose handholds and footholds or, perhaps, the climber may simply fail to successfully climb the route without falling. If \( H \) is a continuous random variable, then in the absence of rescue services expected utility could be defined as,

\[
EU = \int U[m, H(D, R, A), D, R, A, RS = 0] \, dH \quad (5.3)
\]

and utility has arguments income \( m \) and health status \( H \). The climber's ability \( A \) and route attributes \( D \) and \( R \) appear in the health state function and again in the utility function because these attributes may provide utility beyond that associated with health status. The ex ante OP payment that would keep expected utility with rescue services equal to that without rescue services,

\[
\int U[m - OP, H(D, R, A), D, R, A, RS = 1] \, dH
= \int U[m, H(D, R, A), D, R, A, RS = 0] \, dH \quad (5.4)
\]

Equations (5.3) and (5.4) treat the source of uncertainty as a continuously distributed random variable whereas Graham's presentation treated the uncertainty as a discrete, binomial distribution.

Equation (5.4) obscures an important difference between the two approaches, however. In this model the probabilities of each health state are endogenous to the climber because, although he or she is endowed with a
fixed level of ability, the other factors affecting health status (route difficulty and hazard) are choice variables. If we were to revert to the simple binomial outcome (Healthy or Injured), one could recast our model as in equation (5.5):

\[
\begin{align*}
&\{\pi(D, R, A) \times U_{H}\{M-OP, D, R, A, RS=1\}\} + \\
&\{(1-\pi(D, R, A)) \times U_{I}\{M-OP, D, R, A, RS=1\}\} = \\
&\{\pi(D, R, A) \times U_{H}\{M, D, R, A, RS=0\}\} + \\
&\{(1-\pi(D, R, A)) \times U_{I}\{M, D, R, A, RS=0\}\}
\end{align*}
\]

The expression shows that the OP is the payment prior to resolution of the uncertainty: the individual could be injured or healthy and does not know which with certainty, but the OP that equalizes expected utility for the provision of rescue services can nevertheless be determined.

This model embodies a richness of recreational behavior not possible in the standard expected utility model. First, previous analyses of climbers have shown that risk is an important element of the recreational pursuit, and that climbers do not seek complete elimination of risk. The fact that many climbers attempt dangerous routes indicates that at least some climbers derive utility from overcoming the danger. Thus, route attributes enter the utility function directly as choice variables. Second, and perhaps more important from a modeling standpoint, the ‘injury’ probabilities are endogenous to the climber. Again this is consistent with previous research, particularly Jakus and Shaw (1996), who found that climbers who attempted dangerous routes adjusted the probability of injury by attempting routes with a technical difficulty (D), well within the climber’s technical ability (A).

Solving for the OP yields an expression that can be empirically tractable. One can then examine how the OP changes with say, the change in route attributes, or a climber’s ability, that is, the probability of the risky outcome itself. The way the optimal option price payment changes with changes in risk relates directly to risk management programs of interest to policy makers. Smith shows (using our notation) how management decisions affect OP via a change in the risk probability:

\[
d\text{OP} = \left[\frac{U_{H}\{m,H(D, R, A), D, R, A\} - U_{I}\{m,H(D, R, A), D, R, A\}}{\pi(D, R, A) \times U_{H} + [1-\pi(D, R, A)] \times U_{I}}\right] d\pi
\]

where \(U_{H}\) for example, is the partial of the ‘healthy’ utility function with respect to income. Here one can see that the marginal utility of income, whether healthy or injured, is perhaps as important a component of the marginal value as changes in the probabilities or the degree of risk. If the marginal utility of income is constant in both states, then the denominator is quite simple, but this is generally not true (Cook and Graham, 1977); many in the health economics research area would argue that the marginal utility of income is different across the ‘healthy’ and ‘injured’ states. In fact a standard assumption is that the marginal utility of income is zero if dead, unless there are bequest motives built into the utility function.

Note that income and the shape of the expected utility function with respect to route attributes play an important role in determining how OP changes. The existence and sign of the second derivative of the utility function with respect to income or route attributes is one way to determine whether an individual is risk neutral, risk averse, or risk loving. In addition, this derivative determines the relationship between option price and the expected surplus arising from the certainty RUM. For example, if the expected utility function is concave in route attributes, Jensen’s inequality implies that the OP will be greater than the expected surplus, ES. But we are sure of these relationships only when there is this one source of uncertainty. As seen below, there may be other sources of uncertainty and the second derivative with respect to only one variable does not tell the entire story.

Perhaps only when the strict assumptions of expected utility theory are met can one graph a locus of expected utilities, compare these to expected surplus, and analyse differences between OP and ES. Graham makes these assumptions explicitly or implicitly. An important outcome in this framework is that utility functions that are linear in income imply constant marginal utility of income (the second derivative is absent), and hence Graham’s WTP locus is linear, and ES and OP will be the same unless there are other sources of risk. As a preview to what comes below, note that much of the existing RUM recreation demand literature reports surplus measures using utility functions that are linear in income.

The theoretical structure arising from the expected utility model has led many to examine the topic of behavior under risk, but not only a few are empirical studies, and the majority of these do not estimate and report anything related to welfare measures (for example, Cicchetti and Dubin, 1994). To our knowledge most empirical studies that involve welfare estimation assume that stated values under uncertainty yield estimates of the OP and the technique applied is the contingent valuation approach.

Equation (5.4) can be used to derive a deterministic expression for OP and, with careful specification of the source of randomness, a stochastic expression for OP. Larson and Flacco (1991) point this out, but never derive an expression for OP that can be directly estimated using revealed preference (RP) data. Doing so may help one to understand the difficulties in moving from a deterministic to a stochastic OP. While there are many models of non-market valuation currently used in practice, we focus on the
family of discrete choice models currently in vogue for stated preference and/or RP modeling.

4.3 Possible Empirical Models

RP data are most often used in recreation demand models to derive estimable welfare measures. The two most popular approaches seem to be the random utility model (RUM) and the single and multiple-site count data approach, though micro-theoretic systems of a different kind also occasionally appear in the literature. We speculate below on how to extend the RUM to allow for uncertainty, not because we think the RUM is 'best' among the model options, but because it allows a relatively straightforward discussion of the issues.

The conventional RUM assumes that conditional indirect utility functions are random because the investigator is unable to observe all the factors that influence decision making. Expected utility models can, in fact, look like conventional RUMs, but the source of the underlying randomness is quite different. Several scholars have explicitly or implicitly made the claim that the usual binomial logit or MNL assuming certainty can be used to estimate the OP (Edwards, 1988). This is not quite correct, as will be shown below. Alternatively, both Leggett (2002) and Ibañez (2000) introduce uncertainty associated with imperfect information in the context of discrete choice models. These authors follow the Foster and Just (1989) approach of using a restricted expenditure function, where expenditures depend on perceptions but expected utility involves true knowledge. However, the imperfect information framework still maintains the assumption that the individual has perfect information at the time a purchasing decision must be made. The fact that he or she could be 'wrong' when making a choice in an earlier stage because of imperfect information is a different issue from the one with which we are concerned.14

Cameron (2001) differs from the previous studies by generating an expression for OP based on differences in expected utilities. Suppose we let the uncertainty pertain to a change in the random variable q, then we want to examine the expected utility difference over a change in q, or \( E_q[V_1 - V_0] \). Let \( q_1 \) be an improvement over \( q_0 \). Following Cameron, we may start with an indirect utility function specification that is log-linear in income \( m \). Again, this is not necessary, nor is it required to let \( q \) change in various states, but the former allows for income effects while the latter assumption helps motivate the changing conditions that increase or decrease the uncertainty associated with injury or death. For sports such as rock climbing, one could assume \( q \) is the 'injury rate' associated with the risk rating for a climb (the \( R \) or \( X \) discussed above), so that it has a distribution, but is a characteristic for a route. \( A \) is a payment made to or by the individual so that they are indifferent between two levels of utility, where \( V(\cdot) \) is the indirect utility function:

\[
V_1 (m - A, q_1) = \beta_0 \ln(m - A) + \beta_1 q_1 + \epsilon_1
\]

\[
V_0 (m, q_0) = \beta_0 \ln(m) + \beta_1 q_0 + \epsilon_0
\]

where the \( \epsilon \) terms are the conventional measurement error terms. As noted, if one prefers \( q \) can be held constant and the utility difference between health and injured (\( H \) and \( I \)) can be substituted, but to allow for risk, \( H \) and \( I \) must be random variables. Consider the expectation of these utility differences across outcomes for \( q \):

\[
E_q[V_1 - V_0] = \beta_0 \ln [(m - A)/m] + \beta_1 (q_1 - q_0) \, dq + \epsilon
\]

where \( \epsilon = \epsilon_1 - \epsilon_0 \). This shows that the density function for \( q \) enters the calculation of the optimal ex ante payment. Without some source of randomness due to uncertainty we are simply left with the errors arising from the conventional assumptions regarding \( \epsilon \), as before, so that the expected CV is the same as one would be under certainty. If the current state of \( q \), say \( q_0 \), is known, then we are left with the integral on one variable, \( q_1 \), which may collapse to something as simple as the mean, \( E(q_1) \). Cameron, using stated preference data, allows utility to depend on the subjective range in \( q \) provided by respondents. We briefly consider the dependence of the utility function on this range, and other possibilities for the source of uncertainty below.

First, consider the payment \( A \). Because Cameron directly incorporates payment \( A \) into an expected utility framework, OP is the payment \( A \) that solves equation (5.8). Thus, under the simple assumptions made above, OP is quite similar to the CV in the certainty model except OP involves the density on \( q \) for each individual. We can solve equation (5.8) for the OP by setting it equal to zero, making the two expected utilities equal. Again, let the integral collapse to the mean \( E[q_1] \). Solving for OP then yields:

\[
OP = Y - Y \times \exp \{\epsilon/\beta_0 - \beta_1/E[q_1] - q_0]\}
\]

(5.9)

Empirically, it would now be necessary to find \( E[OP] \) for each individual.

The certainty CV has a closed form expression if it is linear in income, so that \( E[CV] \) can be recovered by finding the average over a sample of individuals. The OP in equation (5.9) is a bit more complicated than the measure a linear-in-income model would yield, and nonlinearities may lead to issues in somewhat complex expected welfare measures. Cameron offers a formula for the OP based on a moment generating function. The
exploration of this is tangential to our theme of uncertainty, so we refer the reader to the work of McFadden (1999), Herriges and Kling (1999), and Karlstrom and Morey (2001). Of greater interest in this chapter are assumptions about the nature of the uncertainty and the strength and appropriateness of the EUM framework for application to risky recreation. It is worth exploring whether the concavity in the utility function, perhaps with respect to a risky argument in the utility function other than income, causes difficulties similar to those introduced by non-linearity of income. First, we consider a few variants on the EUM.

4.4 Alternatives to the Expected Utility Model

Many experiments have indicated that an individual's choices can violate expected utility theory, leading to alternative models of risk preferences. The alternatives are numerous and are nicely described by Starmer (2000). Probably the most popular alternative approaches are prospect theory (Kahneman and Tversky, 1979), regret theory (Loomes and Sugden, 1982), and prospective reference theory (Viscusi, 1989). The key concern for alternative theorists seems to be the independence axiom of the EU model. The axiom is frequently inconsistent with observed behavior because it forces the expected utility indifference curves (in probability space) to be parallel lines. Indifference curves may not be parallel if, for example, losses are considered in a much different manner from gains, or if the outcome magnitudes are large enough to cause changes in risk preferences. With rock climbing or other sports where injury or death are legitimate risks, participants may not equally trade off prospects where the worst outcome is a broken ankle and those where the worst outcome is death. In terms of the EU model, a climber would be unlikely to make equal trades where the probability of death is 1 in 10 million, versus a climb with a 1 in 4 chance of death. Empirical models of recreation risk should allow for such richness in behavior. In all alternatives to the EU model there is a gamble taken by an individual but the exact meaning of the resulting welfare measures is a matter of some debate. Some think, for example, that the alternative models yield a different ex ante welfare concept than what Graham intended with his linear-in-probabilities utility function. However, we believe a correct welfare measure is truly an ex ante one, and that consistency with theory should be considered (see Smith, 1992; or Shaw et al. 2002).

4.5 Other Aspects of Modeling Risk and Rock Climbing

Larson (1988) and others raise the possibility that virtually all experiences involve some uncertainty. Recreational fishing does not guarantee a fish caught, a hunter isn't guaranteed to bag an elk, and so on. In the same real sense all climbing is risky, depending on what one considers the goal of climbing, or the risky 'outcome'. If we call reaching the top of the climb the outcome, then each climbing route has the potential for a failure or success, especially if uncertain weather is introduced. Indeed, reaching the 'top' seems to be the thought behind the work by some of those who have explored the risk issues to date (Ewert, 1985; Robinson, 1992; Ewert and Hollenhorst, 1989), but we have seen that the outcome 'completing the route' makes little sense for rock climbing. Would a rock climber be willing to pay something ex ante to avoid failure? The advent of sport climbing, with its great emphasis on gymnastic skills, makes the answer less clear. It is likely some climbers would like success guaranteed, but the very struggle to overcome the difficulties of the route are linked to the enjoyment of the climbing experience – as suggested by our hypothetical example of the climber who purposefully chose to attempt a route whose technical difficulty was at or beyond her limit. Given the many games that climbers play, the analyst must first carefully define the risk to be modeled.

We must also emphasize the link between the probability of failure and the individual's ability and skill. Relative to a less experienced, less skilled climber, the more experienced and skilled climber has the greater probability of completing a climbing route of any given difficulty without injury. As documented in Jakus and Shaw (1996) we know that climbers simply do not ignore these risks. Further, risk-taking attitudes change for routes of different quality, over different days, with different climbing partners and as other factors in a climber's life change over long periods of time (we age, we have children, our willingness to gamble that a rock won't fall from above us changes, and so on). Again, it is likely that highly skilled climbers perceive lower risks of injury or death on a given route relative to less skilled climbers, though we know of no one who has extensively modeled this. Anecdotal evidence exists that a highly skilled climber simply does not believe he or she will fall on particular routes.

The probability of injury or death could be determined in a variety of ways. First, we could use the observed frequency of falls resulting in injury for this, or other climbs. Such statistics are available to a degree, from Accidents in North American Mountaineering, an annual survey published by the American Alpine Club and the Canadian Alpine Club. Many climbing area managers also keep such statistics. We could also rely on survey information reporting the climber's perceived probability of injury or death, but collecting such data would be a formidable task. If the route is rated R or X, then all climbers have some indication of the probability of injury or death, or at least they know that the probability is higher for the R- or X-rated route than for one rated G or PG. Whether
there is a statistical relation between R- and X-rated climbs and the probability of failure remains to be seen. While the EU model uses expert-assessed risk estimates, are these the appropriate probabilities for use in modeling risky recreation? We think not in the case of rock climbing because it is subjective probabilities that directly influence observed choices. Thus, a subjective assessment of probabilities may be more appropriate, as in Cameron (2001); also see Machina 1987; Smith 1992; Shaw et al. (2003).

It is clear that skill and other characteristics of the individual should be linked to risk-taking behavior but this will not be easy. First, it would be inappropriate to assume many or all climbers are risk averse, so that the functional form used in estimation of OP is flexible enough to allow for different risk preferences across individuals. This type of flexibility is not so daunting in certainty models (hence the new wave of modeling individual-specific parameters with simulation methods), but may produce further difficulties in estimation in the context of uncertainty.

Second, analysts often have data linking only the number of climbing trips at a given travel cost to the destination area. While each area may vary a bit in its overall risk attributes, the typical data set would likely end up with too little variation in risks for given travel costs. Data that allows variation in the risk attributes of a given choice must be collected. This implies that we need to more finely tune our demand models and data collection efforts, collecting information on the actual routes chosen because the variation in risk will be across these routes, not areas. In other words, what the climber does during a given trip becomes important, not just where the trip was taken.

All this may suggest that the hedonic travel cost model might be worth renewed interest. We are cognizant of the fact that the hedonic travel cost model (HTC) popularized by Brown and Mendelsohn (1984) is also subject to some debate in the economics literature (see Smith and Kaoru, 1987). Still, the HTC may have strong potential for modeling risky behavior because it could be used to explore the activities on a given trip, and to value each of the various characteristics of the risk recreation experience. As we have suggested, the probability of injury or death (risk) is a characteristic of climbing routes that may explain choices, that is, individuals can be observed to choose from among different climbing routes, just as an investor might change among assets with different risk levels. If travel costs (say approach times) vary across climbing routes we may infer the hedonic price, or the relevant ex ante marginal value for changes in risk from the observed data on route choice. The HTC model could be used to answer the question, 'What change in travel costs is observable at the margin when the risk changes?' The HTC assumes that the climber would trade off risk for travel cost (distance); data can be collected to recover this. Similarly, the marginal implicit prices yielded by the HTC may be used to find the route quality/route risk tradeoff.

5. SUMMARY AND SUGGESTIONS FOR FUTURE RESEARCH

Our exploration has been into risky recreation, particularly the sport of rock climbing. Information collected from rock climbers provides some interesting insights into modeling risky recreation. First, the data run counter to the belief that 'getting to the top' is a primary goal of all climbers, instead showing that 'how' one climbs a route is more important. Thus, the risky outcome is not, in general, the risk of route completion. The data also show that risk-taking is part of the climbing experience.

The theoretical discussion has shown why the risk and uncertainty models yield WTP measures that are different from models that do not incorporate uncertain outcomes. Empirical application of any uncertainty models will require information not normally collected by recreation demand modelers. We need information on choices made during a trip, not just where and how frequently trips are made. Revealed preference data has the potential to be used to model preferences and values under risk, even without use of stated values or preferences. For example, while others have used survey questionnaires that ask individuals to state their WTP for a reduction in risk, we might collect data on the actual route choices (or more generally, some set of activities at the larger area) on a given trip, adding the amount of time it takes to get to a given route (the number of minutes they must walk, or wait to do a particular route). This will likely reveal much about the value for risk reduction. There may be others, but we know of only one study that relies solely on observed behavior to incorporate something about recreation risks (see Jakus and Shaw, 2003).

The interesting policy questions that relate to risk reduction for rock climbers, including emergency rescue management at a climbing area, can probably best be answered using a risky recreation model. Given the cost of rescues at sites such as Yosemite Valley, CA, one might well ask what climbers are willing to pay to reduce risks of injury or death. This could be used to find reasonable insurance payments, if desired.

5.1 Applications to Other Risky Sports

A good deal of what we have learned can be applied to other recreational activities that involve risks of some sort. Perhaps obvious to the reader at
this point, a risk model can also be used explore site or recreation area congestion, about which recreationists might be uncertain (see Jakus and Shaw, 1997; Boxall and Adamowicz, 2000), or any other quality attribute which may involve uncertainty. The approach may also prove useful in the uncertainties associated with hunting or wildlife management. These include the risks of bagging the species or harvesting it, but may also include the risks of driving important species to population levels where their very survival is in question. Several scholars have estimated economic models that allow for some uncertainty in the hunting experience, yet we know of no empirical ones that fully do so.

Analysts need to collect more detailed information on recreation choices and how these relate to risks. Climbers (or other risky recreation participants such as white-water boaters) choose risk levels in three ways. First, they can choose to visit a recreational area with levels of risk across different specific activities that differ from the risks presented at some other area. Second, they can choose different activities within the selected recreation area. If distances vary to each possible activity, we may estimate a risk/dollar trade-off because a person might drive/walk further to be able to recreate in an activity with lower risk. Third, an individual can probably take steps to reduce his or her own risk of injury or death by mitigating activities: wearing a helmet, doing things like top-rope, employing a professional guide, and so on.

Finally, what is a fool? We aren't the first to ask this, as some economists have explored whether willing casino-goers are foolish. No matter what the definition, we think this chapter has shown that in taking risks all climbers are not foolish; indeed the average climber is probably rational is his risk-related choices. Whether this is true for other risky sports remains to be seen. Despite our accumulated knowledge and the thousands of hours that each author has spent hanging from the side of cliffs, we wonder if there is any model based on rational behavior that can explain why some choose to jump off mountain tops wearing a tiny parachute . . .

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NOTES

1. For example, Grijalva et al. (2002b) report the possible harm climbers do to Native American rock art.
2. For example, the 'why' of climbing has been considered by Ewert (1985; 1987) and by Slanger and Rudestam (1997).
3. Mountain and rock climbing drew an estimated 4.2 million participants in the US in 1991, and 17 per cent of the 1992 subscribers of the popular magazine Backpacker said they rock climbed (Lewis, 1993). Staff at a popular US climbing magazine estimate there are 100,000 new climbers each year (Anonymous, The Economist, 1995).
4. One study estimates the willingness to pay (WTP) for white-water boating using the CVM, but does not directly address risk or risk reduction (Boyle et al. 1993). Another study estimates recreation WTP under uncertainty about congestion levels, again using what is more or less the CVM approach (Prince and Ahmed, 1988). Uncertainty or risk has been examined with respect to the probability of fish catch 'success' (Larson, 1988) or bagging big game (Johansson, 1990). We know of no models that use actual behavior or revealed preference (RP) data to derive welfare measures under risk until quite recently (Jakus and Shaw, 2002).
5. Our focus is on rock climbing, as opposed to climbing high mountains such as those found in Alaska or the Himalayas. A key difference is that rock climbing is usually done in fair weather on dry rock, so risks do not include freezing to death in a severe storm, injury or death due to avalanche, ice fall, falling into a crevice, or altitude-related illness. Choice of the type of climbing one does, in itself demonstrates some risk avoidance by certain types of climbers.
6. Some climbers may climb without a rope. This is called 'free soloing'; a fall while free soloing a reasonable distance above the ground will almost certainly result in death or serious injury.
7. The numerical scale for technical difficulty varies in different countries, but in the US the scale runs from the easiest technical climb at 5.0 to the (currently) most difficult, at 5.14. The technical rating is akin to the difficulty rating assigned to dives in diving competitions. Quality ratings usually range from zero stars (low quality) to three stars (high quality). The risk scale is described in the text. Despite different numerical and other classification schemes, the communication of difficulty, quality and risk can be translated from one country to another.
8. Various organizations do keep total statistics on fatalities and injuries. For example, the American Alpine Club reported an average of roughly 30 climbing-related deaths per year in the US during 1990-97. The Mountain Rescue Council states that six climbers were killed in England and Wales in 1993, out of perhaps as many as 150 000 climbers in Britain (Anonymous, The Economist, 1995).
9. This might be compared to the perceived risk of one walking down a flight of stairs, that is, there is some risk associated with falling, but most of us perceive almost no risk because our abilities allow us to negotiate the stairway safely.
10. In addition to technical difficulty and the hazard warning, climbing guidebooks nearly always include a 'quality' rating of zero to three stars. Climbers, especially those climbing in the area for only a short period of time, will focus their efforts on climbs with two or three stars.
11. Here we treat all market goods as a numerarie.
12. Some would argue that because the probabilities are endogenous the expression for OP in (5.2) is not an option price at all. We are not prepared to argue this point in depth; we use the OP terminology because the payment is made prior to the resolution of the uncertainty.
13. This formulation of utility shares the notion put forth by Loewenstein (1999) that climbers derive utility from 'pleasures of skill'. We also note that the climbing community bestows recognition on those who descend difficult and dangerous routes, so that the preference structure is also consistent with what Loewenstein calls 'self-signaling'.
14. Leggett assumes that the CV with imperfect information is still an outcome from utility maximization, where utility is again assumed linear in income.
15. Similarly, if one were interested in modeling white-water kayaking, the important 'location' information may be the particular reach (or reaches) of river that is run as opposed to the put-in point. Further, one may wish to learn if certain sections of the river were portaged rather than boated.

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