Risky Sports and the Value of Information

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Abstract: We develop a theoretical account of how athletes engaged in risky sports value risk-reducing information and use stated-preference data from a sample of backcountry skiers to empirically challenge the predictions of our model. Risk taking in this specific context depends on the athlete's personal attitudes toward risky activities and his strategies to control the risk. Usage of specific information is one strategy of risk control. We estimate the demand value for avalanche information. Caution is however warranted because unobserved factors may jointly affect the athlete's perception of risk and his willingness-to-pay for obtaining the information. We use a recursive two stage estimation approach to account for endogeneity concerns. Our results indicate that the demand value of information increases with wealth and perceived risk and tends to decrease with better skills to control risk and more information about the prevailing field conditions. These results support our theoretical predictions and suggest that variation in athletes' WTP can be explained by their beliefs about the usefulness of information.

Keywords: Self-controlled risk, endogeneity, risky sports, value of information, WTP.

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"I'm not a daredevil, I'm the kind of person who really gears up for a project and I partner with the right people to learn the things that I don't know. Each jump is very well-prepared and it is only when I feel that I did my homework that I jump."

— BASE jumper Felix Baumgartner in a 2007 interview with the Austrian radio station Ö1.

1. Introduction

A puzzling paradox of modern society is that, while we generally agree on the intrinsic value of reducing threats to individual well-being, some of us engage in activities involving a high risk of injury or death (Lyng 2005). Death rates for some risky sports are particularly startling. One out of 77 members of expeditions to the Mount Everest does not return once they climbed higher than the base camp (Firth et al. 2008). Annually, one out of 1,400 members of the U.S. parachute association dies in a skydiving accident (USPA 2011). Among backcountry skiers in Switzerland, the group of athletes we are going to study in the empirical part of this paper, the annual death rate amounts to one in 10,000 skiers (Waeger and Zweifel 2008).

While economists are deeply interested in risk-taking behavior (Schoemaker 1993), the bearing of physical risks outside the market context has not received much attention (Loewenstein 1999). In the psychological literature, the concept of sensation seeking has been developed to describe personality traits that drive some people into risking life and limb in exchange for a thrilling experience (Slanger and Rudestam 1997, Zuckerman 2007). Sociologists have argued that voluntary engagement in high risk sports might be the outcome of acquired preferences for the intense feelings entailed by testing one's skills in the face of danger (Lyng 2005). Both explanations have appeal to economists as they suggest that risky behavior can be captured by incorporating preferences over intense feelings into the athlete's utility function.

There is another remarkable observation on people engaged in risky sports. The majority of them practice their sport in a very controlled and safety concerned manner (Brymer 2005). When it comes to extreme sports such as rope-free climbing, BASE jumping, or steep skiing, athletes carefully prepare attempts and look out for all the relevant information to keep the objectively high risk at a controllable level. This precautionary behavior suggests that athletes do not derive utility from risk taking per se, but rather from what Jeremy Bentham referred to as the pleasures of skill (Loewenstein 1999).

Given that athletes are not reckless risk seekers they should value information that helps them to keep risk at an acceptable level (Hirshleifer and Riley 1992). In the next section, we develop a stylized model of engaging in risky sports and derive propositions on the value of risk-reducing information to athletes who deliberately take physical risks. More specifically, we extend the state-dependent utility model commonly used in the literature on mortality risk valuation (Jones-Lee 1974, Pratt and Zeckhauser 1996, Viscusi 1993, Weinstein et al. 1980) to reflect that athletes can and do actively reduce risk through the use of relevant information.

The main theoretical findings of our model are in line with standard theory. Athletes are willing to pay more for information that helps them to reduce risk, the more risk they face and the wealthier they are. Conversely, they are willing to pay less for the same information, the more skilled or better informed they are. We empirically challenge these findings using stated-preference data from a sample of backcountry skiers whom we inquired about their willingness-to-pay (WTP) for an improved avalanche forecasting service. In section 3, we give a detailed account of the empirical setting, the sample, and the survey. Section 4 presents our econometric strategy and reports on results that support our theoretical predictions. Section 5 concludes with a discussion of the major findings and how they relate to the mortality risk literature.

2. Theoretical Background

We often hear people saying that an accident could have been avoided if only one had known that… So what is the value of risk-reducing information? In the common case where information about the future is uncertain, the agent encounters a problem of valuing imperfect information (Hirshleifer and Riley 1992). He is offered a prediction or forecast that reduces the uncertainty in future decisions. The amount that the agent is willing to pay for receiving this information depends on whether, and by how much, he believes that it will help him in making a utility-maximizing decision.

Information can have a crucial impact on the level of risk taken by athletes and new means of information exchange have made some sports drastically safer. (Think of high altitude mountaineers who call in the latest weather forecast via satellite phone before a peak ascent.) However, how safe a particular endeavor ultimately is does not only depend on information, but also on personal attitudes toward risk and the available technologies to reduce risk (Shogren and Crocker 1991). To model this, we assume that each athlete holds a safety production function that allows him to control risk by means of information *I* and self-protection skills *S*. Knowing about his safety capacity, the athlete chooses the frequency and severity of the sports activity *R*, which we shall call the risky good. The safety production function *s* determines the athlete's subjective probability to meet with an accident:

(1) $p = 1 - \theta(I, R, S)$,

where $\theta : \mathbb{R}_+ \to [0,1)$ is a twice differentiable function so that better skills and more information reduce risk at a diminishing marginal rate (Liu 2004):

(2) $\partial p/\partial I < 0,\ \partial^2 p/\partial I^2 > 0,\ \partial p/\partial S < 0,\ \partial^2 p/\partial S^2 > 0.$

Risking more or more often has a negative effect on safety, but this effect is smaller the better informed or more skilled the athlete is:

(3) $\partial p/\partial R > 0,\ \partial^2 p/\partial R \partial I < 0,\ \partial^2 p/\partial R \partial S < 0.$

The rationale of this assumption is that an athlete with more skills or better information at his command can pursue a more dangerous line, enter steeper terrain, or plunge into bigger waves without increasing the risk to the same extent as a less skilled or worse informed athlete.

The safety production function implies that the athlete is able to dose the amount of risk he is willing to take in exchange for the expected benefits of his attempt (Alhakami and Slovic 1994). To inform this trade-off, he evaluates the subjective expected utility of each option by:

(4) $SEU = [1 - p(I,R,S)]\, u(G,R) + p(I,R,S)\, v(G,R)$,

where $u(G, R)$ denotes utility in the good state and $v(G, R)$ denotes utility in the bad state, i.e. in case of a severe accident. The arguments of the state-dependent utility functions include the utility-entailing risky good R and a composite risk-free good G that reflects the athlete's outside consumption opportunities. (Below, we suppress the arguments to avoid notational clutter.)

We maintain some assumptions common in the health risk literature. We posit that the good state is always preferred to the bad state ($u > v$). Marginal utility is strictly larger in the good state ($\partial u/\partial G > \partial v/\partial G$). (Viscusi and Evans (1990) and Finkelstein et al. (2013) provide empirical support for this assumption). In the good state, marginal utility from consuming G and R is strictly positive ($\partial u/\partial G > 0$, $\partial u/\partial R > 0$) and diminishing ($\partial^2 u/\partial G^2 < 0$, $\partial u^2/\partial R^2 < 0$); in the bad state, marginal utility is non-negative ($\partial v/\partial G \geq 0$, $\partial v/\partial R \geq 0$) and diminishing ($\partial^2 v/\partial G^2 < 0$, $\partial v^2/\partial R^2 < 0$). Further, we assume that the utility from G and R is additively separable ($\partial^2 u/\partial G \partial R = \partial^2 v/\partial G \partial R = 0$) so that the pleasure an athlete receives from a specific sports activity does not depend on wealth.

In the "first-best" world, athletes maximize Eq. (4) with respect to the budget constraint $Y = G + P_I I + P_S S$ to determine the preferred amount of risk to be taken. (Here, Y denotes disposable income, G is the numéraire, and P_I and P_S are per unit prices of information and skill acquirement.) Let L be the Lagrangian of this maximization problem. Then, the first order condition with respect to increments in the risky good R is:

(5) $$\partial L/\partial R = \tfrac{\partial p}{\partial R}(v-u)+(1-p)\tfrac{\partial u}{\partial R}+p\tfrac{\partial v}{\partial R}=0 \leftrightarrow \tfrac{\partial p}{\partial R}(u-v)=p\tfrac{\partial v}{\partial R}+(1-p)\tfrac{\partial u}{\partial R}\,.$$

Hence, maximizing subjective expected utility requires the athlete to behave in such a way that the marginal loss in safety entailed by the activity, weighted by the difference in utility received in the two states of the world, equals the expected marginal utility gained from the risky endeavor. We interpret this as the tradeoff referred to by the popular saying 'no risk, no fun'.

This finding does not tell much about the demand value of risk-reducing information. From the first order condition, $\partial L/\partial I = \partial p/\partial I\ (v - u) - \lambda P_I = 0$, we can only infer that demand depends on the per unit price of information. However, safety-relevant information such as the weather conditions on a specific peak is usually not a market good. To still deduce the value of risk-reducing information we turn to the athlete's WTP for receiving more information given his current state of knowledge I_0. WTP in this context is readily measured by the Hicksian compensating variation C that the athlete is willing to give up in exchange for information:

(6) $$C \equiv -\left.\frac{dG}{dI}\right|_{I=I_0} = \frac{-\tfrac{\partial p}{\partial I}(u-v)}{(1-p)\tfrac{\partial u}{\partial G}+p\tfrac{\partial v}{\partial G}}\,.$$

Eq. (6) extends the standard model of mortality risk valuation in that it allows the athlete to endogenously adjust WTP depending on his personal ability to reduce risk through the provided information. WTP is larger (smaller) than in the standard model if $-\partial p/\partial I > 1$

$(-\partial p / \partial I < 1)$.[1] Apart from the idiosyncratic use of information to reduce risk our model works along the lines of the standard model. That is, increased exposure results in a decrease of the denominator of Eq. (6) and, thus, in an increment of WTP for risk-reducing information (Pratt and Zeckhauser 1996). In Appendix A, we discuss the link to the value of information literature.

Based on the endogenous WTP formulation in Eq. (6), we derive the following propositions on the athletes' demand for risk-reducing information.

PROPOSITION 1. *Athletes who face larger risks have a higher WTP for risk-reducing information than athletes who face smaller risks.*

PROOF. The partial derivative of WTP with respect to risk is:

$$\frac{\partial C}{\partial p} = \frac{-\frac{\partial p}{\partial I}(v-u)\left(\frac{\partial v}{\partial G}-\frac{\partial u}{\partial G}\right)}{\left[(1-p)\frac{\partial u}{\partial G}+p\frac{\partial v}{\partial G}\right]^2} > 0,$$ which follows from Eqs. (2-3) and the assumption that $\partial u/\partial G > \partial v/\partial G$. ■

LEMMA 1. *Athletes who are more frequently exposed have a higher WTP for risk-reducing information than less frequently exposed athletes.*

PROOF. The partial derivative of WTP with respect to the risky good is:

$$\frac{\partial C}{\partial R} = \frac{\left[\frac{\partial^2 p}{\partial I \partial R}(v-u)+\frac{\partial p}{\partial I}\left(\frac{\partial v}{\partial R}-\frac{\partial u}{\partial R}\right)\right]\left[(1-p)\frac{\partial u}{\partial G}+p\frac{\partial v}{\partial G}\right]-\frac{\partial p}{\partial I}(v-u)\frac{\partial p}{\partial R}\left(\frac{\partial v}{\partial G}-\frac{\partial u}{\partial G}\right)}{\left[(1-p)\frac{\partial u}{\partial G}+p\frac{\partial v}{\partial G}\right]^2} > 0,$$

which follows from Eqs. (2-3) and the assumption that $\partial u/\partial G > \partial v/\partial G$. ■

PROPOSITION 2. *Wealthier athletes have a higher WTP for risk-reducing information than less wealthy athletes.*

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[1] This feature of our model is similar to other models in the health risk literature (Liu 2004, Shogren and Stamland 2002, Viscusi 1990).

PROOF. The partial derivative of WTP with respect to the non-risky good is:

$$\frac{\partial C}{\partial G} = \frac{\frac{\partial p}{\partial I}(\frac{\partial v}{\partial G} - \frac{\partial u}{\partial G})[(1-p)\frac{\partial u}{\partial G} + p\frac{\partial v}{\partial G}] - \frac{\partial p}{\partial I}(v-u)[(1-p)\frac{\partial^2 u}{\partial G^2} + p\frac{\partial^2 v}{\partial G^2}]}{[(1-p)\frac{\partial u}{\partial G} + p\frac{\partial v}{\partial G}]^2} > 0,$$

which follows from Eqs. (2-3) and the assumption that $\partial u/\partial G > \partial v/\partial G$. ■

PROPOSITION 3. *Athletes who are better informed about prevailing conditions have a lower WTP for extra-information than less well informed athletes.*

PROOF. The partial derivative of WTP with respect to information I is:

$$\frac{\partial C}{\partial I} = \frac{\frac{\partial^2 p}{\partial I^2}(v-u)[(1-p)\frac{\partial u}{\partial G} + p\frac{\partial v}{\partial G}] - \frac{\partial p}{\partial I}(v-u)[\frac{\partial p}{\partial I}(\frac{\partial v}{\partial G} - \frac{\partial u}{\partial G})]}{[(1-p)\frac{\partial u}{\partial G} + p\frac{\partial v}{\partial G}]^2} < 0,$$ which follows from Eqs. (2-3). ■

PROPOSITION 4. *High-skilled athletes have a lower WTP for risk-reducing information than low-skilled athletes.*

PROOF. *See Appendix B.*

In the following we are going to scrutinize these propositions based on a dataset of Swiss backcountry skiers. Backcountry skiing has become a popular sport in Europe (Holler 2007) and North America (Stethem et al. 2003) despite its proneness to avalanche risk. The annual death toll among backcountry skiers in Switzerland is about 20, implying a statistical mortality risk of 10^{-4} per year (Waeger and Zweifel 2008). About 90% of the victims either trigger or are buried in an avalanche released by another group member (McClung and Schaerer 2006). Moreover, skiers may control their risk through the use of information provided by avalanche forecasts (Tremper 2001). The high degree of self-control makes backcountry skier a soliciting population to study the value of risk-reducing information.

3. Empirical Study

Avalanche forecasts convey information about the conditions in the backcountry and rate risk based on an internationally standardized danger scale from ONE to FIVE, where ONE means generally safe conditions and FIVE means very high avalanche risk (McClung and Schaerer 2006). In Switzerland, the national avalanche forecasting service issues a daily forecast during the winter. This forecast follows a default script providing (i) general information on the weather, snow conditions and snowpack during the past 24 hours, (ii) the latest weather developments relevant to avalanche danger, (iii) the avalanche danger forecast for various regions indicating the danger level for the following day, and (iv) a danger outlook for the next two days.[2]

To date, avalanche information is provided as a quasi-public good and, because skiers have free access, one cannot deduce a market price for risk-reducing information. For this reason revealed-preference methods are not feasible. Instead we draw on stated-preference data to elicit skiers' value of risk-reducing avalanche information. We do so cautiously since we are well aware of the potential problems that may arise from the hypothetical nature of stated preferences (List and Gallet 2001, Loomis 2011).

Of course, it would be daunting to ask people about their WTP for a good to which they have already free access. Thus, we let respondents evaluate a hypothetical, but realistic, enhancement of the current avalanche forecasting service that would provide more detailed local information over a longer forecast range. And we reminded respondents of the free access they have to the current forecasting service.

Some remarks on avalanche information are in order. We stress that avalanche forecasts are often misperceived. A recent study found that while two-thirds of the surveyed skiers knew

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[2] The Swiss avalanche forecasting system is accessible under: www.slf.ch.

the prevailing avalanche danger scale, only one-third could recall specific information on danger spots (Schwiersch et al. 2005). Moreover, professional guides and recreationists differ considerably in their use of avalanche information to inform site choices (Haegeli et al. 2010). Other studies confirm the differences between experts and novices in terms of knowledge, training, rescue skills, and behavior in dangerous situations.

However, better skills do not always result in lower risk. McCammon (2004) identified six heuristic fallacies that let even experienced skiers misjudge avalanche risks. Skiers take more risk in familiar terrain; they risk more once they have judged the terrain as safe; they risk more when they can earn respect from peers; they risk more in the presence of others; they take disproportionate risks to access virgin snow; and they ascribe risk-controlling skills to group leaders which these leaders might or might not have.

These field level findings are in perfect agreement with the value of information theory—it is not the information that is of worth, it is what you do with the information (Hirshleifer and Riley 1992). Economic wisdom holds that the value provided by the enhanced forecasts is readily measured by the maximum amount a skier would be willing to pay for accessing the extra information (Hilton 1981). The demand value is private to the skier in that it depends on his perceived accuracy of the information and on his ability to make use of it in reducing risk. Hence, it is important to understand how skiers perceive avalanche risk and how better information impacts their decision behavior in the terrain (Tremper 2001). Arguably, a survey approach is the only way to learn more about these things.

3.1 Survey

We administered an online survey to a convenience sample of skiers whom we recruited from among the visitors of the web site that distributes the daily avalanche forecast for

Switzerland. Participation was voluntary, unpaid, and anonymous. The survey was offered in any of four languages (German, French, English or Italian) and comprised four broad sections.

Section A inquired about the respondent's skills and experience in backcountry skiing and whether the respondent is a (semi-)professional mountain guide. Section B included a series of questions about the respondents' usual efforts to reduce avalanche risk. We also inquired about the attendance of avalanche safety classes, the use of safety equipment, and the frequency of rescue search practicing. In section C, respondents rated the existing avalanche forecasting service. We asked them to judge its information value on an ordinal scale from low to high. This led to the question whether the respondent had ever been caught in an avalanche. The section closed with some further questions on avalanche prevention strategies.

At the heart of the survey we elicited WTP for an improved version of the current avalanche forecast. In the prelude, all respondents were told about the hypothetical enhancement of the current avalanche forecasting service that would provide more detailed information. Respondents were then randomly assigned to a treatment or control variant of the survey. The control group did not receive information about the expected benefits of the enhanced forecast and directly moved on to the WTP question. By contrast, the treatment group was explicitly told that on average twenty skiers die each year in avalanche accidents and that the enhanced forecast could reduce this death toll to either sixteen or fourteen fatalities per year (see Appendix C).

Respondents were queried about their WTP for the enhanced forecasting service using a double-bounded dichotomous choice (DBDC) format (Carson and Hanemann 2005). Specifically, they were asked whether they would be willing to pay a randomly assigned bid amount from Table 1 for a one-year subscription to the enhanced forecasting service. If respondents stated that they would be willing to pay the initial bid b^{I}, we questioned them again at a higher amount b^H. If they refused, we asked whether they would be willing to pay a lower amount b^L. Respondents who declined both bids were asked to report a maximum WTP value b^P.

<INSERT TABLE 1>

Directly after the WTP question we asked respondents to compare their personal risk with the statistical risk of dying in an avalanche and to state whether they believe it was lower, the same as, or higher than that of the average backcountry skier. In section D, we asked additional questions about their risk tolerance and elicited socio-demographic information.

3.2 Sample

The survey was online from February through April 2009. During this period a total of 1,210 persons took the survey. We deleted records with invalid IP addresses or complete item non-response and excluded respondents who we identified through their email addresses to work for the research institute that issues the avalanche forecasts. This left us with a sample of n = 1,134 valid responses. Below, we highlight the most remarkable features of the sample. A full description of the sample characteristics is given in Table 2.

<INSERT TABLE 2>

Males account for 87% of the sample. On average respondents received 16 years of formal schooling. Almost 70% of the respondents live in Switzerland. They earn a monthly mean net household income of roughly CHF 7,700, which is somewhat above the 2009 population average of CHF 6,700 (BFS 2011). Slightly less than half of the respondents actually lead groups. Two-thirds of the respondents report to be moderately experienced backcountry skiers; about 28% believe they are advanced backcountry skiers and the remaining 6% are beginners. Half of the respondents judge their personal risk of dying in an avalanche to be about the same as that of the average backcountry skier; 42% (8%) of them think it is lower (higher).

Since the survey was posted online, we have no means to assure that our sample is representative of the universe of backcountry skiers. Comparison to a large population survey on sports (Lamprecht et al. 2008) suggest that with respect to age and the number of backcountry trips our sample is very similar to the average Swiss backcountry skier. The only exception is the share of males who are overrepresented in our sample (87% vs. 60%).

Respondents were recruited while retrieving the avalanche forecast and, thus, the sample might over-represent skiers who care relatively more about safety. If that was the case, one would expect the sample's WTP for the enhanced forecast to be higher than that of the general population of backcountry skiers. We cannot rule out such a self-selection bias, but since our sample closely resembles that of a user survey on the Swiss avalanche forecasting service, which did not mentioned fees, we can at least rule out that self-selection occurred as result of the announced pay service. In any case, our sample seems too specific to permit extrapolations to other information services.

4. Econometric Model

Answers to our WTP question provide a mix of point and interval data. Some 205 respondents (18%) stated that they were not willing to pay anything at all for access to the enhanced forecasting service. Another 212 respondents (19%) stated an exact and positive amount. Answers of 717 respondents (63%) implied intervals of WTP. An appropriate econometric strategy to analyze such a sample is the spike model by Kristrom (1997), which specifies the latent WTP *C** as a mixture distribution of the following form:

$$(7) \qquad F(C^*;\pi) = \begin{cases} \pi, & \text{if } C = 0 \\ H(C), & \text{if } C^* > 0, \end{cases}$$

where $\pi \in [0,1]$ is the probability to observe a zero WTP and $H(C)$ is a continuous and increasing function in C such that $\lim_{C \to 0} H(C) = \pi$ and $\lim_{C \to \infty} H(C) = 1$.

To estimate the spike model researchers commonly specify a parametric distribution of the latent WTP, which they evaluate using maximum likelihood methods (Carson and Hanemann 2005). This approach works fine as long as respondents take the announced risk reduction at face value. However, if unobserved factors affect the perceived risk *and* the WTP at the same time, then WTP estimates will be distorted (Konishi and Adachi 2011, Whitehead 2005).

This is exactly the situation our theoretical model predicts. Skiers decide about the frequency and seriousness of their backcountry trips and use skills and information to control their personal risk p_i as defined by Eq. (1). It seems natural that their WTP for better avalanche information is influenced by how much risk they believe to face. Hence, we want to estimate the WTP distribution *conditional* on a set of covariates that capture the skiers' perceived risk and their ability to control risk.

We do so by setting up a recursive mixed-process model (Roodman 2011). The model treats the WTP elicitation as the outcome of the joint decision over two latent variables, the response to the WTP question for which we have interval or point data and the ordinal risk estimates. Formally, let C_i^* denote respondent i's latent WTP and p_i^* his unobserved subjective risk. Now, define two limited dependent variables C_i and p_i so that:

$$\text{(8a)} \qquad C_i = \begin{cases} C_i^{\text{int}} & \text{if } b_i^{\text{H}} > C_i^* \geq b_i^{\text{L}} \\ C_i^{\text{left}} & \text{if } \infty > C_i^* \geq b_i^{\text{H}} \\ C_i^{\text{right}} & \text{if } b_i^{\text{L}} > C_i^* \geq 0 \\ C_i^{\text{point}} & \text{if } C_i^* = b_i^{\text{P}} \end{cases}$$

and:

(8b) $$p_i = \begin{cases} p_i^{\text{low}} & \text{if } p_i^* < \overline{p} \\ \overline{p} & \text{if } p_i^* = \overline{p} \\ p_i^{\text{high}} & \text{if } p_i^* > \overline{p} \end{cases}$$

with $\overline{p}$ denoting the avalanche mortality risk to the average backcountry skier.[3]

Let $\mathbf{X}_{1i}$ and $\mathbf{X}_{2i}$ be $1 \times K_1$ and $1 \times K_2$ row vectors of exogenous variables. Then, a pair of simultaneous equations can be set up for the continuous latent random variables C_i^* and p_i^*:

(9a) $$C_i^* = \mathbf{X}_{1i}\boldsymbol{\alpha}_1 + p_i\beta_1 + p_i^*\gamma_1 + \varepsilon_{1i},$$

(9b) $$p_i^* = \mathbf{X}_{2i}\boldsymbol{\alpha}_2 + C_i\beta_2 + C_i^*\gamma_2 + \varepsilon_{2i},$$

with $E[\varepsilon_{ji}] = 0, E[\varepsilon_{ji}^2] = \sigma_j, j = 1,2; E[\varepsilon_{1i}\varepsilon_{2i}] = \sigma_{12}, i = 1,\dots,n; E[\varepsilon_{1i}\varepsilon_{2i'}] = 0, i \neq i'$. The chronology of the survey approach allows us to restrict some of the parameters of Eq. (9b) to zero (Konishi and Adachi 2011). It is safe to assume that $\beta_2 = \gamma_2 = 0$ because neither respondent i's true WTP to obtain risk-reducing information in the future nor his answer to the corresponding WTP question can logically affect the perceived risk p_i^* of past and/or current activities. In consequence, the system of equations is recursive.

Both coefficients γ_1 and β_1 in Eq. (9a) capture potentially relevant effects. The former measures the extent to which latent factors that affect the skier's risk estimate also influence his WTP for risk-reducing information; the latter measures the extent to which the skier's WTP is affected by the stated risk itself. As Heckman (1978) shows, both effects can jointly enter the model because substitution for p_i^* results in a recursive system of simultaneous equations:

[3] In the empirical analysis, we present results for both an ordered probit specification and a simple probit specification where we include $p_i^{\text{low}} = 1$ iff $p_i^* < \overline{p}$.

(10a) $C_i^* = \mathbf{X}_{1i}\boldsymbol{\alpha}_1 + \mathbf{X}_{2i}\boldsymbol{\theta} + p_i\beta_1 + \xi_{1i}$,

(10b) $p_i^* = \mathbf{X}_{2i}\boldsymbol{\alpha}_2 + \xi_{2i}$,

where $\boldsymbol{\theta} = \boldsymbol{\alpha}_2\gamma_1$, $\xi_{1i} = \varepsilon_{1i} + \varepsilon_{2i}\gamma_1$, and $\xi_{2i} = \varepsilon_{2i}$.

Assuming that ξ_{1i} and ξ_{2i} are bivariate normally distributed as BVN(0, 0, 1, 1, ρ), the mixed-process model is fully identified and provides means to test the hypothesized effect of endogenous risk on the demand value for risk-reducing information. If the errors of the WTP and risk equation are uncorrelated, i.e. $\rho = 0$, the model boils down to the conventional spike model (Kristrom 1997). If on the other hand $\rho \neq 0$, it yields the conditional mean $\mathrm{E}[C^*|\mathbf{X}_1, \mathbf{X}_2, \Pi]$ and median $\mathrm{M}[C^*|\mathbf{X}_1, \mathbf{X}_2, \Pi]$ WTP.

One drawback of the model as shown in Eq. (10) is that its identification rests on the joint normality assumption and might be fragile in the absence of exclusion restrictions. A natural strategy for better identification is to exclude a vector of controls which affect WTP only through their effect on risk perceptions (Wilde 2000). We therefore partition $\mathbf{X}_{2i}\{\mathbf{x}_i, \mathbf{z}_i\}$ such that $\mathbf{x}_i$ is a $1 \times K_{\mathbf{x}}$ row vector of exogenous variables included in the WTP equation and $\mathbf{z}_i$ is a $1 \times K_{\mathbf{z}}$ row vector of excluded exogenous variables that support identification.

5. Results

We begin the presentation of the results with a check of the internal validity of WTP responses. We do so by examining whether the percentage of <YES> responses declines monotonically with the initial bid amount (Alberini 2005). Table 3 shows that this is indeed the case, confirming that the demand for the extra information decreases with increasing prices. The frequency of pairs of responses to the initial and follow-up bids indicates that the sample is generally well behaved. YY sequences accounted for 19.4% of the sample, NY for 14.7%, YN for 29.2%, and NN for 36.7%.

<INSERT TABLE 3>

Proportions of <YES> responses across initial bids are equal in the control and treatment groups and we do not find evidence for a relationship between the initial bid amount and the tendency to report zero WTP.[4] In the Appendix (Table D1) we present results of a probit regression, indicating that respondents were more likely to declare zero WTP for the improved forecasting system when they did not use the current forecasting system, thought it was of little information value, or believed that their risk was below average. This is encouraging as it suggests that respondents carefully considered the good to be valued.

5.1 Regression Results

We now turn to the regression analysis. Table 4 presents three different specifications of the simultaneous equations model fitted with Stata's `cmp` routine (Roodman 2011). All of them assume that latent WTP is lognormally distributed.[5] Model I is the conventional spike model, imposing that factors which determine the respondents' WTP are uncorrelated with unobserved factors that may affect their perceived risk. Models II (first stage probit) and III (first stage ordered probit) relax this assumption by allowing for correlation between perceived risk and WTP. That is, we treat ρ as an estimable parameter and can therefore test whether respondents who rated their risk to be higher/lower than average had a higher/lower WTP than those who rated their risk to be average.

<INSERT TABLE 4>

[4] The percentages of zero WTP responses in the groups of respondents who received initial bids of CHF 15, 40, 50, 100 and 200 were 20%, 23%, 18%, 20% and 19%.
[5] A closeness test (Vuong 1989) on the spike model suggests that the lognormal distribution fits our empirical data significantly better than other distributional forms.

We augmented the vectors $\mathbf{X}_{1i}$ and $\mathbf{X}_{2i}$ with individual information to capture differences in WTP and perceived risk that arise from the characteristics of the respondent. The WTP equation contained characteristics of the skier as well as dummies indicating whether he had received the control or treatment variant of the survey.

Besides the skier's characteristics, the risk equation contained further regressors that indicate safety relevant behavior. We posit that these regressors affect the WTP for risk-reducing information *only* through the respondent's perceived risk. E.g., skiers who make many trips to the backcountry are more exposed to avalanche risk than skiers who do only few trips (TRIPS). If they also perceive their risk to be higher, then we expect them to be willing to pay more for the enhanced forecasting system than less exposed skiers. A similar reasoning applies to the other excluded exogenous regressors (SCORE, YOE, SAFEC, PRACT_HIGH, PRACT_LOW, STEQUIP, ADDEQ, DEFENS, CAUGHT).[6] All of them do not increase WTP for information per se, but may affect it through their effect on skier's risk perception.

Model I deliberately assumes independence between perceived risk and WTP for risk-reducing information. The results suggest that only three variables are significant predictors of WTP. In favor of Proposition 2, WTP increases by ~5% for every additional CHF 1,000 in monthly household income (HHINC). Swiss residents (SWISS) are willing to pay almost 50% more for the improved forecasting service. In support of Proposition 4, respondents who stated that the current forecasts provide useful information always or most of the times (VOI_LARGE) have a 26% higher WTP than those who stated that these forecasts provide useful information only some of the times. Other covariates including the skill and risk variables are insignificant.

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[6] The SCORE variable measures the skier's risk propensity based on answers to six behavioral questions, which inquired about the respondent's preferences for descents, difficult terrain, physical challenge, powder snow, and road safety on hazardous mountain roads. All other excluded exogenous variables are described in Table 2.

Perceived avalanche risk increases with the frequency (TRIPS) and seriousness of past trips (SCORE). Residents (SWISS) assessed their risk of dying in an avalanche to be smaller than did non residents; as did skiers who behaved defensively under uncertain snow conditions (DEFENS), believed to be healthier than their age mates (HEALTH), and had practiced rescue operations three or more times in the last winter (PRACT_HIGH).

The WTP equation of Model II confirms these results with one notable exception. Skiers who rated their risk to be below average (RISK_LOW) have a three times smaller value for the improved forecasting system than skiers who rated their risk to be average or above average. The correlation coefficient is large ($\rho = -0.56$) and significant, indicating that perceived risk affects the WTP for risk-reducing information.

In model III two additional regressors become (weakly) significant. In support of Proposition 3, highly skilled skiers (SKILLS_HIGH) are willing to pay 15% less for the risk-reducing information; those who rated their risk to be higher than that of the average skier (RISK_HIGH) are willing to pay one and a half times more for risk-reducing information. The correlation coefficient of model III remains large ($\rho = -0.48$) and significant confirming that indicators of self-assessed avalanche risk should not be seen as exogenous regressors to explain WTP for risk-reducing information.

5.2 Scope and Robustness Tests

The WTP equation incorporated dummies indicating whether or not the respondent received information about the expected effectiveness of the improved forecasting service (TREAT); and, if informed, whether the annual risk reduction was four (RR_BASE = 1) or six (RR_LARGE = 1) avoided fatalities among 200,000 skiers. Although the signs of the respective coefficients are plausible, we found that neither the disclosure of information nor the size of the risk reduction had a significant impact on WTP. Two factors may explain the statistical insignificance of the treatments.

First, respondents were not told that the improved forecasting system would decrease their personal risk. Instead, the risk reduction was expressed in terms of avoided fatalities per year. Clearly, this metric is related to the average skier. Yet, the results in Table 4 suggest that more than 50% of the respondents considered their personal risk to be higher or lower than average. It seems that these respondents used their *own* risk to inform their payment decision rather than the provided information about the risk reduction expected to the *average* skier. Second, respondents evaluated small reductions in risk (4:200,000 vs. 6:200,000) and it is well possible that they perceived these risk reductions as approximately equal in size (Corso et al. 2001).

To examine external validity, we compared our WTP estimates to value of statistical life (VSL) estimates obtained in a similar context. In Table 5, we provide summary statistics of the VSL implied by the answers of those respondents who received information about the average risk reduction and stated that their personal risk was equal to that of the average skier.[7] We contrast these estimates with benchmark VSL values by Leiter and Pruckner (2009), who recently studied avalanche mortality risk in Austria. Our WTP estimates imply somewhat higher VSL values, but still in the same order of magnitude.

<INSERT TABLE 5>

As a further robustness check we repeated the regression analysis on restricted samples. We excluded zero WTP responses (Table D2), non-residents (Table D3), and skiers who did less than five backcountry trips last winter (Table D4). Due to the limited number of observations, the

[7] We lack a risk denominator to calculate the VSL value for respondents who stated a lower or higher risk than that of the average skier or those who received the control treatment.

SKILL_HIGH and RISK_HIGH variables are no longer statistically significant in these restricted samples, but the general thrust of the results remains unchanged.

6. Discussion

Some people risk their life to ski a virgin slope, to climb a remote peak, or to basejump from a skyscraper. Such activities seem reckless and the public often meets them with a shake of the head. Indeed, deliberate risk taking is not reconcilable with the standard economics model of health risk valuation, in which some sort of compensation is required for accepting any risk increment. We have extended the standard health risk model (Viscusi 1993) to reflect that athletes receive utility from a risky leisure activity. Our model assumes that athletes use idiosyncratic skills to control risk, which helps explaining why it is not irrational that athletes, who voluntarily take large risks, strive at the same time to minimize these risks.

Based on the model, we have derived four propositions on the demand value of risk-reducing information. These propositions have strong ties to the existing literature. As in the standard VSL model, wealthier athletes should be willing to pay more for an information that provides means for risk reduction (Hammitt and Treich 2007). However, the actual risk reduction depends crucially on the athlete's ability to make use of the received information. Because our model presumes that both skills and information help to reduce risk, athletes should be willing to pay less for information the better skilled they are and the more they know about the prevailing conditions (Shogren and Stamland 2002). And as in the standard model, athletes should be willing to pay more for risk-reducing information when they face larger risks (Pratt and Zeckhauser 1996).

We have scrutinized these propositions using a stated preference survey of backcountry skiers, a group of athletes who bear a considerable risk of dying. We find strong empirical support for the propositions 1-3. Indeed, WTP for risk-reducing information increased with household income and was substantially smaller (larger) among skiers who rated their personal risk to be lower (higher) than average. The more valuable a skier judged the information provided by the current avalanche forecasts, the more he was willing to pay for the improved forecasting system. Empirical support for Proposition 4 (skill level) is somewhat weaker, but high skilled skiers at least tended to have a lower WTP for the improved forecasting system than average or low skilled skiers.

Athletes have the means to make use of skills, equipment, and information, in ways that allow them to take risks others would not survive. Mastering these risks is what gives them pleasure. Therefore, high-risk athletes value information to control risk and—importantly—they base the value of this information on their perceived risk rather than on the population average risk. This highlights the importance of accounting for endogenous beliefs over risk.

Tables

Table 1. Initial and follow-up bid amounts (in CHF).

Initial bid (b^{I})	Follow-up bid if <YES> (b^{H})	Follow-up bid if <NO> (b^{L})
15	40	7
40	50	15
50	100	40
100	200	50
200	300	100

Table 2. Descriptive sample statistics (N = 1,134).

Variables	Description	Mean	SD	Min.	Max.
ADEQUIP	Use of advanced safety and rescue equipment	0.31	0.46	0	1
AGE	Age of the respondent in years	40.61	12.02	14	76
CAUGHT	Respondent had been caught in avalanche	0.19	0.40	0	1
CLEAR_BASE [a]	Current forecast is often clear	0.40	0.49	0	1
CLEAR_HIGH	Current forecast is always/mostly clear	0.53	0.50	0	1
CLEAR_LOW	Current forecast is only some of the time clear	0.07	0.25	0	1
DEFENS	Defensive behavior under uncertain snow conditions	0.27	0.44	0	1
EDUC	Educational attainment in years	16.00	2.58	4	21
FAMILY	Respondent has family	0.71	0.45	0	1
HEALTH	Health better than that of age-mates	0.68	0.47	0	1
HHINC	Monthly household income in 1,000 CHF	7.70	3.24	2.5	13
MALE	Respondent is male	0.87	0.33	0	1
LEAD	Respondent leads groups of skiers	0.49	0.50	0	1
PRACT_BASE [a]	Practiced 1-2 times with beacon in pre-season	0.64	0.48	0	1
PRACT_HIGH	Practiced ≥ 3 times with beacon in pre-season	0.21	0.41	0	1
PRACT_LOW	Did not practice with beacon in pre-season	0.14	0.35	0	1
RISK_BASE [a]	Personal risk equal to that of average skier	0.49	0.50	0	1
RISK_HIGH	Personal risk higher than that of average skier	0.08	0.27	0	1
RISK_LOW	Personal risk lower than that of average skier	0.42	0.49	0	1
SAFEC	Respondent attended safety class	0.32	0.47	0	1
SCORE [b]	Risk propensity score	1.69	1.38	0	6
SKILLS_BASE [a]	Respondent is an intermediate in backcountry skiing	0.66	0.47	0	1
SKILLS_HIGH	Respondent is a proficient in backcountry skiing	0.28	0.45	0	1
SKILLS_LOW	Respondent is a beginner in backcountry skiing	0.06	0.23	0	1
STEQUIP	Use of standard safety and rescue equipment	0.92	0.26	0	1
SWISS	Respondent is a Swiss resident	0.69	0.46	0	1
TREAT	Information about risk reduction is disclosed	0.50	0.50	0	1
RR_BASE [a]	Proposed risk reduction is 4 in 200’0000	0.23	0.42	0	1
RR_HIGH	Proposed risk reduction is 6 in 200’0000	0.27	0.44	0	1
TRIPS	Backcountry trips during the past winter season	15.57	8.17	0	25
USE	Forecasts always/mostly consulted before trip	0.98	0.15	0	1
VOI_BASE [a]	Forecast gives valuable information: often	0.40	0.49	0	1
VOI_HIGH	Forecast gives valuable information: always/mostly	0.52	0.50	0	1
VOI_LOW	Forecast gives valuable information: some of the times	0.08	0.27	0	1
YOE	Years of experience	14.63	8.36	0	25

[a] Baseline reference levels not included in the regression analysis; [b] the SCORE variable measures the skier’s risk propensity based on answers to six behavioral questions, which inquired about the respondent’s preferences for descents, difficult terrain, physical challenge, powder snow, and road safety on hazardous mountain roads.

Table 3. Frequency and percentage share of <YES> responses to the initial bid (*N* = 1,134).

Initial bid (in CHF)	Number of respondents (*N*)	<YES> responses
15	254	182 (72%)
40	234	133 (57%)
50	222	116 (52%)
100	219	76 (35%)
200	205	43 (21%)

Table 4. Regression results.

	MODEL I		MODEL II		MODEL III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Risk equation						
CUT1	0.611	0.513	-0.222	0.569	0.601	0.503
CUT2	2.359 ***	0.518			2.343 **	0.502
ADEQUIP	0.028	0.080	0.034	0.082	0.044	0.074
AGE	0.015	0.021	0.020	0.023	0.018	0.021
AGE^2	-0.038 *	0.023	-0.045 *	0.026	-0.041 *	0.024
CAUGHT	0.121	0.096	0.097	0.102	0.148	0.094
DEFENS	-0.132	0.085	-0.047	0.094	-0.047	0.094
EDUC	0.019	0.014	0.004	0.015	0.020	0.015
FAMILY	-0.110	0.090	-0.151	0.100	-0.132	0.087
HEALTH	-0.165 **	0.078	-0.236 ***	0.087	-0.168 **	0.076
LEAD	-0.026	0.079	-0.047	0.086	-0.054	0.079
MALE	0.138	0.111	0.118	0.121	0.158	0.109
PRACT_HIGH	-0.213 **	0.096	-0.083	0.103	-0.127	0.100
PRACT_LOW	0.082	0.121	0.036	0.131	-0.031	0.125
SAFEC	0.106	0.091	0.158 *	0.092	0.133	0.087
SCORE	0.076 ***	0.028	0.018	0.029	0.057 *	0.030
SKILL_HIGH	0.105	0.090	0.022	0.100	0.091	0.090
SKILL_LOW	-0.088	0.172	-0.170	0.185	-0.119	0.178
STEQUIP	0.167	0.167	0.222	0.172	0.109	0.171
SWISS	-0.343 ***	0.078	-0.371 ***	0.087	-0.338 ***	0.077
TRIPS	0.030 ***	0.005	0.032 ***	0.006	0.031 ***	0.005
USE	0.088	0.264	-0.053	0.277	0.076	0.225
YOE	0.000	0.006	-0.001	0.006	-0.002	0.005
WTP equation						
CONSTANT	2.828 ***	0.537	3.244 ***	0.583	3.170 ***	0.577
SCALE	1.039	0.028	1.144 **	0.067	1.136 *	0.079
AGE	0.029	0.021	0.020	0.023	0.026	0.023
AGE^2	-0.034	0.023	-0.016	0.027	-0.023	0.027
CLEAR_HIGH	-0.046	0.079	-0.043	0.077	-0.044	0.077
CLEAR_LOW	0.183	0.158	0.205	0.173	0.212	0.174
EDUC	-0.014	0.015	-0.013	0.016	-0.021	0.016
FAMILY	-0.003	0.093	0.071	0.101	0.064	0.101
HEALTH	0.051	0.080	0.113	0.082	0.090	0.081
HHINC	0.048 ***	0.013	0.046 ***	0.012	0.046 ***	0.013
LEAD	0.084	0.076	0.053	0.083	0.065	0.083
MALE	-0.054	0.109	-0.100	0.109	-0.138	0.109
RISK_HIGH	0.077	0.147			0.809 **	0.315
RISK_LOW	-0.108	0.079	-1.113 ***	0.278	-0.876 ***	0.296
RR_LARGE	0.093	0.105	0.093	0.109	0.090	0.108
SKILL_HIGH	-0.057	0.088	-0.119	0.096	-0.168 *	0.102
SKILL_LOW	-0.087	0.155	0.087	0.162	0.073	0.163
SWISS	0.281 ***	0.084	0.390 ***	0.095	0.390 ***	0.098
TREAT	-0.025	0.093	-0.028	0.095	-0.023	0.095
USE	0.203	0.295	0.147	0.324	0.097	0.312
VOI_HIGH	0.228 ***	0.078	0.226 ***	0.076	0.236 ***	0.076
VOI_LOW	-0.223	0.162	-0.193	0.182	-0.216	0.187
Model Characteristics						
RHO	0.000	fixed	-0.556 ***	0.127	-0.484 ***	0.147
Log-likelihood RISK eq.	-957.07					
Log-likelihood WTP eq.	-1400.65					
Log-likelihood	-2357.71		-2107.03		-2353.98	
Observations	1134		1134		1134	

*** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

Table 5. Comparison of mean and median VSL values (in million CHF) against the benchmark VSL values by Leiter and Pruckner (2009: Table 6), inflation adjusted and converted to 2009 CHF.

	Mean VSL (95%-CI) [a]	Median VSL (95%-CI) [a]
Benchmark VSL values by Leiter and Pruckner based on a risk reduction of 1:42,500	3.17 (2.49-3.85)	1.43 (1.11-1.75)
VSL values implied by Model II [a] assuming a risk reduction of 1:40,000	5.42 (1.76-9.08)	2.82 (0.92-4.72)
VSL values implied by Model III [a] assuming a risk reduction of 1:40,000	4.59 (1.40-7.79)	2.41 (0.73-4.09)

[a] VSL values based on the answers of respondents who received either of the two treatment variants of the survey and rated their risk to be equal to the average skier.

Appendix

Appendix A. Theoretic link to the Value of Information literature

Our theoretical model treats the self-control of risk as a black box. However, economic theory provides a clear idea of how athletes should make use of information to reduce their risk (Hirshleifer and Riley 1992). We seek to make this link more apparent. Consider the example of a backcountry skier who does not have free access to the avalanche forecast and asks himself whether the forecast would be worth paying for. Before every trip, the skier has some assumptions about the prevailing conditions. We denote his prior subjective assessment of the probability of an avalanche accident by p_0.

Let $i = \{1, 2, \ldots, n\}$ be a set of signals conveyed by the avalanche forecast. The skier is assumed to update his initial assessment of avalanche risk, i.e. his beliefs about p_0, in a Bayesian way (Hirshleifer and Riley 1992). Ex ante, he does not know which signal he will receive. Hence he determines a subjective probability π_i of receiving the specific signal i, which is conditional on receiving signal i given that it is an accurate description of the prevailing conditions ($\pi_{i|\Theta}$) and on not receiving signal i when it does not accurately describe the prevailing conditions ($1 - \pi_{i|\Theta}$):

(A1) $\quad \pi_i = \pi_{i|\Theta} p_0 + (1-\pi_{i|\Theta})(1-p_0)$,

where Θ denotes prevailing conditions or "states of the world". After receiving the signal, the skier may determine the posterior probability of an accident $p_{\Theta|i}$ by updating his prior risk assessment, taking the presumed diagnostic accuracy of the forecasting system into account:

(A2) $\quad p_{\Theta|i} = \pi_{i|\Theta} p_0 / \pi_i$.

Based on $p_{\Theta|i}$ the skier may decide to revise the planned route, to avoid a particular slope, or to cancel a backcountry trip outright. That is, he decides over the set of actions $a = \{1, 2, \ldots, x\}$

that are relevant to his safety. The demand value of information provided by signal i can readily be measured by the compensating variation c_t that makes the skier indifferent between receiving and not receiving the signal before a specific trip t (Hilton 1981):

(A3) $$E_i\{\max_a[(1-p_{\Theta|i})u_a(G-c_t,R)+p_{\Theta|i}v_a(G-c_t,R)]\}=\max_a[(1-p_0)u_a(G,R)+p_0v_a(G,R)].$$

where c_t is an *ex-ante* measure of the skier's WTP for information that makes the backcountry trip t safer.

Next, we demonstrate that summed over all BC trips t = 1, 2, …, T where access to information is of value the compensating variation equals the skier's demand value C for seasonal access to the enhanced information system as derived by Eq. (6), i.e. $\sum_t c_t = C.$ We assume that the skier's utility derived from risky sports activities R and from the non-risky good G is additive with state dependent utility functions $u(G, R)$ = 10 + 5 log(G + R) and $v(G, R)$ = log(G + R) borrowed from Pratt and Zeckhauser (1996). Standing in front of a steep slope, the skier can choose between two actions: go on (a_1) or turn around (a_2). Let $p_{0|a_1}=0.1$ be the skier's prior probability of an avalanche accident when entering the slope. By turning back he eliminates avalanche risk to zero, i.e. $p_{0|a_2}=0$. The right-hand side of Eq. (A3) becomes the following maximization problem:

(A4) $$\max_{a\in 1,2}[a_1:9+4.6\log(G+R);a_2:10+5\log(G)].$$

Now consider the case where the skier accessed the forecast, which provided him with either of two signals for steep slopes—safe (i_1) or risky (i_2). Based on his experience with the forecasting system he determines the likelihood $\pi_{i_1|u}$ of receiving signal i_1 when it is safe to enter the slope ($\Theta = u$), and the likelihood $\pi_{i_2|v}$ of receiving signal i_2 when it is dangerous ($\Theta = v$).

Since forecasting services tend to minimize false positives (type I errors), which usually entail more severe consequences than false negatives (type II errors), we assume that $\pi_{i_2|v} > \pi_{i_1|u}$, e.g., $\pi_{i_1|u} = 0.5$ and $\pi_{i_2|v} = 0.8$. Based on the assessment of these likelihoods the skier updates the initial risk assessment, deriving posterior probabilities of ending up in an accident conditional on the received signal i_1 or i_2 and having continued the trip (a_1):

(A5) $$p_{v|i_1,a_1} = \frac{\pi_{i_1|v} p_{0,a_1}}{\pi_{i_1|v} p_{0,a_1} + \pi_{i_1|u}(1-p_{0,a_1})} = \frac{(1-\pi_{i_2|v}) p_{0,a_1}}{(1-\pi_{i_2|v}) p_{0,a_1} + \pi_{i_1|u}(1-p_{0,a_1})} = 0.043\text{, and}$$

(A6) $$p_{v|i_2,a_1} = \frac{\pi_{i_2|v} p_{0,a_1}}{\pi_{i_2|v} p_{0,a_1} + \pi_{i_2|u}(1-p_{0,a_1})} = \frac{\pi_{i_2|v} p_{0,a_1}}{\pi_{i_2|v} p_{0,a_1} + (1-\pi_{i_1|u})(1-p_{0,a_1})} = 0.151.$$

The left-hand side of Eq. (A3) then becomes the following maximization problem:

(A7) $$E_{i,t}\{\max_{a\in 1,2}[a_1 \mid i_1\!: 9.6 + 4.8\log(G - c_t + R); a_1 \mid i_2\!: 8.5 + 4.3\log(G - c_t + R); a_2\!: 10 + 5\log(G - c_t)].$$

After incorporating the skier's subjective probabilities of receiving signal i_1 or i_2—say $\pi_{i_1} = 0.8$ and $\pi_{i_2} = 0.2$—into Eq. (A7), the decision problem of Eq. (A3) simplifies to:

(A8) $$\max_{a\in 1,2}[9.4 + 4.7\log(G - c_t + R); 10 + 5\log(G - c_t)] = \max_{a\in 1,2}[9 + 4.6\log(G + R); 10 + 5\log(G)]$$

From Eq. (A8) it follows that c_t is the compensating amount that makes the skier indifferent between receiving and not receiving information that helps him to choose the best feasible action in the course of a particular backcountry trip t.

Appendix B. Proof of Proposition 4

PROOF. To show that the partial derivative of WTP with respect to the level of skills S is negative, we take the first order condition:

$$\text{(B1)} \qquad \frac{\partial C}{\partial S} = \frac{\frac{\partial^2 p}{\partial I \partial S}(v-u)\,[(1-p)\frac{\partial u}{\partial G} + p\,\frac{\partial v}{\partial G}] - [\frac{\partial p}{\partial I}(v-u)\frac{\partial p}{\partial S}(\frac{\partial v}{\partial G} - \frac{\partial u}{\partial G})]}{[(1-p)\frac{\partial u}{\partial G} + p\,\frac{\partial v}{\partial G}]^2} < 0,$$

and solve for:

$$\text{(B2)} \qquad \frac{\partial p}{\partial I}\frac{\partial p}{\partial S} > \frac{\partial^2 p}{\partial I \partial S}\left[p - \frac{\partial u}{\partial G}\Big/\left(\frac{\partial u}{\partial G} - \frac{\partial v}{\partial G}\right)\right].$$

If skills and information are substitutes or independent risk reduction technologies ($\partial^2 p/\partial I \partial S \geq 0$), the inequality in Eq. (B2) follows from the common assumption that $\partial u/\partial G > \partial v/\partial G$ (Finkelstein et al. 2013, Viscusi and Evans 1990). If skills and information are complements ($\partial^2 p/\partial I \partial S < 0$), then Eq. (B2) can be re-arranged to yield:

$$\text{(B3)} \qquad \underbrace{p - \frac{\partial p}{\partial I}\frac{\partial p}{\partial S}\Big/\frac{\partial^2 p}{\partial I \partial S} - 1}_{\psi} > \frac{\partial v}{\partial G}\Big/\left(\frac{\partial u}{\partial G} - \frac{\partial v}{\partial G}\right).$$

Under the complementarity assumption between skills and information, all endogenous risk functions in line with Eqs. (2-3) imply that $-\frac{\partial p}{\partial I}\frac{\partial p}{\partial Z}\Big/\frac{\partial^2 p}{\partial I \partial Z} \geq 1$ and, in turn, $\psi > 0$. Rearranging yields the following sufficient condition for Proposition 1 to hold: $\frac{\partial u}{\partial G}\Big/\frac{\partial v}{\partial G} > \frac{1+\psi}{\psi}$. In words, the marginal utility of consumption in the good state relative to the marginal utility in the bad state must be larger than the threshold value $\frac{1+\psi}{\psi}$. For this to be the case, either $\frac{\partial u}{\partial G}\Big/\frac{\partial v}{\partial G}$ or ψ have to be sufficiently large. If we consider that accidents in risky sports often result in death, it seems reasonable to assume that $\frac{\partial u}{\partial G} \gg \frac{\partial v}{\partial G}$ and, hence, the condition is fulfilled in all relevant cases. ■

Appendix C. Exact wording of the treatments and WTP questions

Treatment text. The avalanche forecast is currently provided free of charge to users of the WSL Institute for Snow and Avalanche Research SLF in Davos. The forecast for avalanche danger is valid for the next 24 hours. Suppose it was possible to develop an enhanced forecasting service with more detailed information on avalanche danger on a regional and local scale, and forecasts of avalanche danger for the next 48 hours. The improved avalanche information would support many backcountry and out of bound skiers/snowboarders in their decision-making. Currently, about 20 fatalities occur every winter in avalanche-related accidents. It is estimated that the enhanced and extended avalanche bulletin would reduce the number of avalanche-related fatalities to 16 [14] per winter. Suppose that to help defray the cost of developing and providing these enhanced forecasting services, it was necessary to charge users for accessing them on the SLF web site, via phone, MMS, WAP, and Teletext. You would still have access to the basic 24 hour forecast for free. Would you be willing to pay b^{I} CHF for a one-year subscription with unlimited access to this enhanced avalanche bulletin with more detailed local conditions and forecasts extended to 48 hours?

Control text. The avalanche forecast is currently provided free of charge to users of the WSL Institute for Snow and Avalanche Research SLF in Davos. The forecast for avalanche danger is valid for the next 24 hours. Suppose it was possible to develop an enhanced forecasting service with more detailed information on avalanche danger on a regional and local scale, and forecasts of avalanche danger for the next 48 hours. Suppose that to help defray the cost of developing and providing these enhanced forecasting services, it was necessary to charge users for accessing them on the SLF web site, via phone, MMS, WAP, and Teletext. You would still have access to the basic 24 hour forecast for free. Would you be willing to pay b^{I} CHF for a one-year subscription with unlimited access to this enhanced avalanche bulletin with more detailed local conditions and forecasts extended to 48 hours?

Appendix D. Robustness tests

Table D1. Probit regression of zero WTP.

	Coef.		Std. Err.
(Intercept)	-0.868		0.628
AGE	0.022		0.025
AGE^2	-0.017		0.028
EDUC	-0.020		0.018
CLEAR_HIGH	0.077		0.097
CLEAR_LOW	-0.272		0.211
FAMILY	-0.047		0.119
HEALTH	-0.087		0.099
HHINC	0.000		0.016
LEAD	0.056		0.094
MALE	0.226		0.153
RISK_HIGH	0.259		0.167
RISK_LOW	0.228	**	0.096
SKILL_HIGH	0.277	***	0.101
SKILL_LOW	-0.349		0.240
SWISS	-0.034		0.101
TREAT	0.014		0.112
TREAT_HIGH	-0.075		0.127
USE	-0.647	**	0.300
VOI_HIGH	-0.070		0.097
VOI_LOW	0.501	***	0.172
Model characteristics			
Log- likelihood	-511.077		
Observations	1,134		
McFadden R^2	0.06		

*** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

Table D2. Sample restricted to non-zero WTP responses (N = 929).

	MODEL I		MODEL II		MODEL III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Risk equation						
CUT1	0.399	0.584	0.030	0.665	0.409	0.580
CUT2	2.212 ***	0.588			2.212 ***	0.584
ADEQUIP	0.009	0.088	0.037	0.090	0.034	0.080
AGE	0.024	0.023	0.036	0.026	0.028	0.023
AGE^2	-0.047 *	0.026	-0.062 **	0.030	-0.052 **	0.026
CAUGHT	0.058	0.108	0.073	0.113	0.105	0.099
DEFENS	-0.174 *	0.093	-0.060	0.104	-0.059	0.091
EDUC	0.019	0.016	-0.001	0.017	0.020	0.016
FAMILY	-0.133	0.099	-0.205 *	0.108	-0.160	0.098
HEALTH	-0.208 **	0.086	-0.268 ***	0.096	-0.210 **	0.086
LEAD	-0.013	0.086	-0.038	0.094	-0.044	0.085
MALE	0.037	0.119	0.002	0.130	0.055	0.118
PRACT_HIGH	-0.217 **	0.108	-0.098	0.116	-0.101	0.104
PRACT_LOW	0.010	0.134	-0.055	0.141	-0.119	0.125
SAFEC	0.046	0.099	0.127	0.100	0.088	0.090
SCORE	0.081 ***	0.031	0.013	0.032	0.055 *	0.030
SKILL_HIGH	0.077	0.101	-0.037	0.111	0.059	0.099
SKILL_LOW	-0.198	0.185	-0.277	0.199	-0.248	0.184
STEQUIP	0.174	0.183	0.227	0.189	0.098	0.168
SWISS	-0.340 ***	0.087	-0.395 ***	0.097	-0.332 ***	0.087
TRIPS	0.031 ***	0.006	0.033 ***	0.006	0.031 ***	0.006
USE	-0.089	0.331	-0.280	0.376	-0.086	0.332
YOE	-0.001	0.006	-0.002	0.007	-0.004	0.006
WTP equation						
CONSTANT	2.828 ***	0.537	3.162 ***	0.597	3.121 ***	0.592
SCALE	1.039	0.028	1.142 **	0.067	1.149 *	0.085
AGE	0.029	0.021	0.014	0.024	0.023	0.023
AGE^2	-0.034	0.023	-0.009	0.028	-0.018	0.026
CLEAR_HIGH	-0.046	0.079	-0.040	0.077	-0.042	0.079
CLEAR_LOW	0.183	0.158	0.207	0.173	0.218	0.158
EDUC	-0.014	0.015	-0.011	0.016	-0.021	0.016
FAMILY	-0.003	0.093	0.091	0.104	0.081	0.105
HEALTH	0.051	0.080	0.122	0.084	0.109	0.089
HHINC	0.048 ***	0.013	0.046 ***	0.012	0.045 ***	0.013
LEAD	0.084	0.076	0.049	0.085	0.060	0.084
MALE	-0.054	0.109	-0.051	0.110	-0.096	0.120
RISK_HIGH	0.077	0.147			0.878 ***	0.292
RISK_LOW	-0.108	0.079	-1.114 ***	0.282	-0.937 ***	0.270
RR_LARGE	-0.057	0.088	0.092	0.109	-0.156	0.101
SKILL_HIGH	-0.087	0.155	-0.095	0.097	0.134	0.184
SKILL_LOW	0.281 ***	0.084	0.132	0.169	0.400 ***	0.098
SWISS	-0.025	0.093	0.398 ***	0.098	-0.023	0.092
TREAT	0.093	0.105	-0.028	0.095	0.087	0.104
USE	0.203	0.295	0.220	0.342	0.153	0.324
VOI_HIGH	0.228 ***	0.078	0.223 ***	0.076	0.233 ***	0.078
VOI_LOW	-0.223	0.162	-0.194	0.182	-0.215	0.161
Model Characteristics						
RHO	0.000	Fixed	-0.556 ***	0.128	-0.512 ***	0.149
Log-likelihood RISK eq.	-774.78					
Log-likelihood WTP eq.	-1400.65					
Log-likelihood	-2175.43		-1971.96		-2171.57	
Observations	929		929		929	

*** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

Table D3. Sample restricted to residents (N = 783).

	MODEL I		MODEL II		MODEL III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Risk equation						
CUT1	1.181	0.636	-0.889	0.690	1.186 *	0.611
CUT2	2.910 ***	0.643			2.898 ***	0.612
ADEQUIP	-0.059	0.098	-0.027	0.113	0.009	0.103
AGE	0.018	0.026	0.021	0.288	0.020	0.027
AGE^2	-0.042	0.029	-0.046	0.032	-0.043	0.030
CAUGHT	0.173	0.226	0.262	0.231	0.148	0.224
DEFENS	-0.316 ***	0.120	-0.210	0.134	-0.215	0.135
EDUC	0.164	0.147	0.089	0.172	0.028	0.159
FAMILY	0.080	0.118	0.078	0.132	0.146	0.120
HEALTH	-0.144	0.107	-0.080	0.132	-0.044	0.128
LEAD	0.019	0.017	0.009	0.019	0.022	0.017
MALE	-0.177	0.109	-0.213 *	0.119	-0.197 *	0.108
PRACT_HIGH	-0.109	0.096	-0.196 *	0.107	-0.111	0.095
PRACT_LOW	0.064	0.095	0.004	0.102	0.032	0.094
SAFEC	0.199	0.133	0.185	0.144	0.230 *	0.129
SCORE	0.067	0.115	0.167	0.122	0.120	0.116
SKILL_HIGH	0.063 *	0.034	0.010	0.037	0.043	0.038
SKILL_LOW	0.226 **	0.115	0.158	0.127	0.191 *	0.114
STEQUIP	0.032	0.205	-0.008	0.222	-0.046	0.212
TRIPS	0.033 ***	0.007	0.036 ***	0.007	0.032 ***	0.007
USE	0.204	0.338	0.054	0.349	0.172	0.301
YOE	-0.003	0.007	-0.006	0.008	-0.008	0.007
WTP equation						
CONSTANT	3.433 ***	0.655	3.920 ***	0.688	3.959 ***	0.700
SCALE	1.018	0.034	1.092	0.078	1.124	0.117
AGE	-0.009	0.025	-0.016	0.027	-0.011	0.027
AGE^2	0.009	0.028	0.023	0.031	0.020	0.032
CLEAR_HIGH	0.002	0.018	0.000	0.018	-0.008	0.020
CLEAR_LOW	0.117	0.112	0.211 *	0.120	0.226 *	0.127
EDUC	-0.029	0.093	-0.030	0.093	-0.025	0.093
FAMILY	-0.065	0.199	-0.064	0.203	-0.053	0.204
HEALTH	0.015	0.097	0.052	0.093	0.028	0.095
HHINC	0.047 ***	0.015	0.046 ***	0.015	0.046 ***	0.015
LEAD	0.081	0.180			0.835 *	0.469
MALE	-0.049	0.127	-0.036	0.131	-0.038	0.132
RISK_HIGH	0.041	0.090	0.004	0.097	-0.005	0.101
RISK_LOW	-0.123	0.093	-0.943 *	0.402	-0.919 **	0.440
RR_LARGE	-0.018	0.128	-0.077	0.131	-0.130	0.142
SKILL_HIGH	-0.037	0.109	-0.116	0.120	-0.172	0.137
SKILL_LOW	-0.065	0.180	0.022	0.190	0.042	0.197
TREAT	0.009	0.112	0.003	0.115	-0.003	0.115
USE	0.308	0.377	0.258	0.358	0.218	0.343
VOI_HIGH	0.264 ***	0.093	0.266	0.092	0.277 ***	0.092
VOI_LOW	-0.277	0.209	-0.241	0.235	-0.247	0.244
Model Characteristics						
RHO	0.000	fixed	-0.476 *	0.202	-0.506 **	0.218
Log-likelihood RISK eq.	-647.32					
Log-likelihood WTP eq.	-954.31					
Log-likelihood	-1601.62		-1444.76		-1599.53	
Observations	783		783		783	

*** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

Table D4. Sample restricted to skiers who did at least five trips in the last winter ($N = 978$).

	MODEL I		MODEL II		MODEL III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Risk equation						
CUT1	0.757	0.642	-0.350	0.750	0.857	0.610
CUT2	2.518 ***	0.646			2.610 ***	0.609
ADEQUIP	0.034	0.084	0.036	0.088	0.046	0.079
AGE	0.022	0.022	0.031	0.025	0.025	0.023
AGE^2	-0.046 *	0.025	-0.056 **	0.028	-0.049 *	0.026
CAUGHT	0.165	0.197	0.237	0.195	0.152	0.181
DEFENS	-0.210 **	0.099	-0.077	0.110	-0.123	0.113
EDUC	0.193	0.135	0.181	0.155	0.076	0.148
FAMILY	0.159	0.099	0.129	0.107	0.182 *	0.097
HEALTH	-0.148	0.092	-0.048	0.116	-0.040	0.122
LEAD	0.031 **	0.015	0.015	0.016	0.032 **	0.015
MALE	-0.091	0.097	-0.112	0.109	-0.112	0.096
PRACT_HIGH	-0.196 **	0.085	-0.274 ***	0.097	-0.195 **	0.083
PRACT_LOW	-0.012	0.083	-0.029	0.092	-0.036	0.084
SAFEC	0.198	0.123	0.202	0.134	0.224 *	0.120
SCORE	0.097	0.099	0.145	0.102	0.124	0.095
SKILL_HIGH	0.082 ***	0.030	0.030	0.031	0.068 **	0.034
SKILL_LOW	0.137	0.092	0.059	0.102	0.126	0.092
STEQUIP	-0.145	0.247	-0.166	0.273	-0.195	0.227
SWISS	-0.321 ***	0.084	-0.345 ***	0.094	-0.316 ***	0.083
TRIPS	0.026 ***	0.006	0.028 ***	0.007	0.028 ***	0.006
USE	-0.076	0.376	-0.378	0.463	-0.078	0.317
YOE	-0.001	0.006	-0.005	0.007	-0.005	0.006
WTP equation						
CONSTANT	3.198 ***	0.688	3.619 ***	0.738	3.539 ***	0.711
SCALE	1.032	0.031	1.140	0.097	1.136	0.121
AGE	0.020	0.023	0.007	0.026	0.015	0.026
AGE^2	-0.028	0.025	-0.005	0.031	-0.013	0.031
CLEAR_HIGH	-0.010	0.016	-0.014	0.017	-0.023	0.019
CLEAR_LOW	0.096	0.102	0.159	0.111	0.154	0.113
EDUC	-0.029	0.084	-0.033	0.083	-0.033	0.083
FAMILY	-0.035	0.179	-0.058	0.186	-0.037	0.185
HEALTH	0.062	0.088	0.150	0.096	0.124	0.095
HHINC	0.051 ***	0.014	0.051 ***	0.013	0.050 ***	0.013
LEAD	0.055	0.150			0.807 *	0.454
MALE	0.068	0.112	0.072	0.114	0.070	0.114
RISK_HIGH	0.061	0.081	0.044	0.090	0.054	0.089
RISK_LOW	-0.056	0.086	-1.090 **	0.437	-0.850 *	0.461
RR_LARGE	-0.083	0.121	-0.168	0.125	-0.200	0.132
SKILL_HIGH	-0.085	0.091	-0.140	0.100	-0.190 *	0.111
SKILL_LOW	-0.091	0.225	0.034	0.245	0.058	0.245
SWISS	0.277 ***	0.089	0.375 ***	0.106	0.379 ***	0.112
TREAT	-0.011	0.100	-0.017	0.101	-0.011	0.101
USE	-0.031	0.455	0.086	0.432	0.012	0.399
VOI_HIGH	0.214 **	0.083	0.222 ***	0.082	0.231 ***	0.082
VOI_LOW	-0.266	0.179	-0.249	0.200	-0.275	0.208
Model Characteristics						
RHO	0.000	fixed	-0.563 **	0.195	-0.492 *	0.225
Log-likelihood RISK eq.	-840.21					
Log-likelihood WTP eq.	-1192.15					
Log-likelihood	-2032.35		-1799.66		-2030.47	
Observations	978		978		978	

*** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

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