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Behavioral probabilities

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Abstract This article introduces the concept of behavioral probabilities, along with an econometric procedure for jointly estimating these probabilities as well as individual utility functions. Behavioral probabilities that guide decisions differ from posterior probabilities that are reported after receiving risk information. The underlying process that generates behavioral probabilities reflects a behavioral anomaly as the new risk information takes on an excessive role. While utility function estimates are consistent with theoretical predictions, considering behavioral probabilities alters their implications.

Keywords Behavioral probability · Risk perceptions · Expected utility · Bayesian

JEL Classification D8, I10, J17, J28

Studies of choice under uncertainty examine the structure of individual choices involving a given set of lotteries. The usual implicit assumption is that the stated probabilities in the experiment are taken at face value and guide individual decisions. The researcher's task then is to analyze whether these decisions are consistent with expected utility theory or with some other choice model.

In contrast to this standard modeling assumption, the prospective reference theory model presented in Viscusi (1989) suggests that respondents do not treat the probabilities presented to them as fully informative. Rather, people combine the stated risk information with their prior risk beliefs in a Bayesian fashion to form the posterior probabilities that will guide their behavior. In the case where prior probabilities are 'flat,' or identical for all lottery outcomes,

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the model predicts a wide range of behavioral anomalies, such as the Allais Paradox, the representativeness heuristic, the overweighting of low probabilities, and the isolation effect.

A possible solution to the divergence between behavioral probabilities and stated probabilities is to elicit from respondents information about what they perceive to be the posterior probabilities. That was the approach taken in Viscusi and Evans (1990) in an exploration of experimental results focusing on worker responses to chemical labeling. Reported posterior probabilities may more accurately characterize the probabilistic beliefs guiding individual behavior than does probability information presented in an experimental context. However, even reported assessed probabilities may not fully capture the probabilities that actually drive decisions. What people report as their risk beliefs may not be the same as the risk beliefs that do in fact influence their behavior.[1]

In this paper, we use the reported posterior probabilities to help specify a parametric function for behavioral probabilities. We then specify an econometric model that jointly estimates the parameters of this function as well as the structure of utility functions. Thus, the utility function estimates will be based on the behavioral probabilities revealed through individual choices.

Section 1 introduces the data from a worker survey that we will use to explore the linkage between the probabilities respondents assess after being shown hazard warnings and the probabilities revealed through their decisions. Section 2 presents the econometric model that jointly estimates behavioral probabilities and state-dependent utility functions. Section 3 discusses the estimated relationship between the behavioral probabilities and the probabilities reported by the individuals themselves. Use of behavioral probabilities rather than reported posterior probabilities affects the estimated structure of the utility functions by raising the marginal utility of income in the good health state by just under 5 percent. However, analysis of behavioral probabilities has a greater effect on the compensating differential implied for risk, as these estimated amounts increase by 11 percent to as much as 175 percent. Our methodology also enables researchers to estimate the relative information weight that respondents place on their prior beliefs and the new information presented during the experiment when forming their behavioral probabilities.

1. The worker survey data

The analysis we present below could be applied in a variety of contexts, but for concreteness, our development will focus on a sample of chemical workers who took part in an experimental study of responses to chemical labeling.[2] The data set includes information on workers' prior risk beliefs, posterior risk beliefs after being shown a hazard warning label, their current wage rate, and the wage increase they would require to work on the job after receiving the information.

In particular, we will utilize a data set on 249 chemical workers from four major chemical plants. Each of the workers in the sample currently worked with chemicals as part of his or

[1] A considerable recent literature has explored different aspects of perceived risks and the relationship of risk beliefs to policy preferences and behavior. See Smith et al. (2001), Chilton et al. (2002), Lundborg and Lindgren (2004), Cameron (2005), Hurley and Shogren (2005), and Sloan, Khwaja, and Chung (2006).

[2] See Viscusi and O'Connor (1984), Viscusi (1992), Viscusi and Evans (1990), and Evans and Viscusi (1993) for previous analyses with this data set. A consumer product application in a similar vein appears in Evans and Viscusi (1991, 1993).

Table 1 Summary of chemical labeling experiment

Variables elicited by the survey	Chemical 1: Choroaceto-phenone	Chemical 2: Asbestos	Chemical 3: TNT
Prior Risk Assessment p	0.10	0.09	0.10
Posterior Risk Assessment z_j after Being Given the Warning	0.18	0.26	0.31
Compensating Differential $\delta_j y$ Required to Stay on the Risky Job*	$1,919	$2,996	$5,158
Sample Size	84	87	78

*Compensating differential is additional annual compensation required in 1982 dollars.

her job. The workers reported their prior risk assessments of the probability p that they would be involved in a nonfatal job injury.[3] The risk measure was a quantitative linear probability scale that the respondents viewed as equivalent to the riskiness of their current jobs. Thus, the approach was to use a reference lottery for nonfatal job injuries to establish the metric for assessing the attractiveness of a new job.

Each respondent was then shown a hazard warning for chemical j ($j = 1, 2, 3$) that the respondent was told would replace the chemicals currently used on the job. Chemical 1 is chloroacetophenone, which is an industrial chemical that causes tearing. Chemical 2 is asbestos, which is a major carcinogen that has been the subject of numerous major lawsuits. Chemical 3 is TNT, which is a well-known and quite powerful explosive.[4] The warning labels complied with the standard warnings format for industrial chemicals in the United States.

After being shown the hazard warning for one of the three chemicals, each respondent used the same linear scale as for the prior probability to rate the posterior risk probability associated with the job. We designate the value of the reported posterior risk belief associated with the job as z_j. The risk s_j that the worker associated with the hazard warning was not assessed as part of the survey, but it will be estimated. The worker was then asked the additional amount of annual compensation that he or she would require to work with the chemical described on the warning label. The reservation wage question was in terms of the percentage δ_j of the respondent's income y that was needed to compensate for the risk posed by chemical j.

In Table 1, we report for each of the three chemicals the prior risk probabilities (p), the posterior risk beliefs (z_j), and the wage differential δ_j. The prior risks are almost identical for each of these groups, ranging from 0.09 to 0.10 in annual injury risk. Workers considered the hazard warning for one of the three chemicals. For each group of chemicals, on average workers assessed these risks as being higher than they were for the job before receiving the warning, where these risk values ranged from a low of 0.18 for chloroacetophenone to 0.31 for TNT. This pattern of posterior risk beliefs is reasonable given the risks associated with each chemical. The annual compensating differential values, which appear in the third row of Table 1, exhibit a pattern similar to that of the posterior risk beliefs, in that Chemical 1 has the lowest value and Chemical 3 has the highest value.

[3] The baseline information pertains to the worker's actual job, and the hazard warning information pertains to hypothetical products that might replace the chemicals with which they now work.

[4] A fourth group of workers not analyzed in this paper considered the chemical sodium bicarbonate, which was the control labeling treatment. As household baking soda is comparatively harmless, workers did not require a compensating differential to work with this chemical.

2. Modeling of behavioral probabilities

In Viscusi and Evans (1990), we used the information from the three risky chemicals to assess the structure of worker utility functions implied by their reservation wage choices and their reported assessed posterior risk beliefs z_j. To do so, we assumed that the posterior probability risk information respondents reported was the probability information that actually governed their decisions. However, this assumption may not be true. Individuals may report a particular probability level, but they may reveal through their decisions a quite different behavioral probability. By failing to recognize that the stated probabilities given by respondents may not reflect the actual probabilities implicit in their decision, the estimation results in Viscusi and Evans (1990) forced any such influences to be captured by the structure of the utility functions.

In this paper we generalize this approach by permitting the probabilities revealed by behavior to differ from the probabilities reported by respondents. Thus, the econometric technique that we introduce in this paper explicitly estimates the probabilities that individuals reveal through their decisions, making it possible to examine how these probabilities relate to the probabilities stated by respondents. Thus, it will be possible to compare the value of the posterior job risk z_j assessed by respondents with the value of the behavioral probabilities q_j implied by the compensating differential decisions. Model estimates will then allow us to examine the correspondence between stated and behavioral probabilities.

Assume that individuals' posterior risk assessments can be characterized by the beta distribution, which can take a wide variety of shapes.[5] Let γ be the precision of the prior job risk assessment p and ξ_j be the precision associated with the warning for chemical j, which has an associated implied risk of s_j. The worker reported the values of the assessed posterior probability z_j and the prior probability p, but did not report the other coefficients discussed below. The equation for the behavioral probability value q_j is given by

$$q_j = \frac{\gamma p + \xi_j s_j}{\gamma + \xi_j} = \gamma_j' p + \xi_j' s_j, \tag{1}$$

where

$$\gamma_j' = \frac{\gamma}{\gamma + \xi_j} \quad \text{and} \quad \xi_j' = \frac{\xi}{\gamma + \xi_j}. \tag{2}$$

The case where the value of the precision term ξ_j is identical for each chemical is a special case that will be estimated for the pooled sample, leading to the equation

$$q_j = \gamma' p + \xi' s_j, \tag{3}$$

where

$$\gamma' = \frac{\gamma}{\gamma + \xi} \quad \text{and} \quad \xi' = \frac{\xi}{\gamma + \xi}. \tag{4}$$

[5] This formulation appears in Viscusi (1985, 1989, 1998) and in Viscusi and O'Connor (1984). See also Smith et al. (2001), Lundborg and Lindgren (2004), and Sloan, Khwaja, and Chung (2006).

The two possible health state outcomes are suffering a job injury or remaining healthy. A job injury may alter the structure of the utility function, affecting both the utility level and the marginal utility. Viscusi and Evans (1990) used logarithmic utility functions of worker income Y, where the utility of being healthy equaled $\nu \ln Y$, and the utility of being injured equaled $\ln Y$.[6] The hypothesis is that the level of utility is greater when the worker is healthy than when injured, or $\nu > 1$. Empirical estimates for the full sample based on the workers' reported probabilities implied a value of $\nu = 1.082$.

The survey set up a scenario in which respondents were asked to equate the expected utility of the initial job with prior risk p to the utility of the job described by the chemical label that implied a risk s_j and led to a behavioral risk probability q_j. To achieve this equality, respondents were asked the percentage wage increase δ_j that would equate the initial job with income y and the new job. Let the tax rate be t, the earnings replacement rate under workers' compensation be r, and asterisks denote the post-warning values for t and r. The survey equated the expected utility for the original and modified jobs, or

$$(1-p)\upsilon \ln[y(1-t)] + p \ln(yr) = (1-q_j)\upsilon \ln[y(1+\delta_j)(1-t^*)] + q_j \ln[y(1+\delta_j)r^*]. \tag{5}$$

This equation can be solved for δ to obtain the estimating equation for δ_j. The result is that

$$\delta_j = \exp\left[\frac{m_1 - m_2}{(1-q_j)\alpha + q_j}\right] - 1 + \varepsilon, \tag{6}$$

where

$$m_1 = (1-p)\upsilon \ln[y(1-t)] + p \ln[yr], \tag{7}$$

$$m_2 = (1-q_j)\upsilon \ln[y(1-t^*)] + q_j \ln[yr^*], \tag{8}$$

and the utility function parameter ν is a function of education and firm-specific job experience (tenure), or

$$\upsilon = \upsilon_0 + \upsilon_{\text{Ed}}\,\text{Education} + \upsilon_{\text{Ten}}\text{Tenure}. \tag{9}$$

We estimated Equation 6 using nonlinear least squares, where ε is assumed to be i.i.d. with mean 0 and finite variance, and Equations 7–9 define the components of Equation 6.

The first column in Table 2 presents the results for the pooled sample in which the precision parameters are identical for all three chemicals, but the risk levels differ (Equation 3), and the final three columns permit these parameters to vary across chemicals (Equation 1). The results for the pooled sample in column 1 of Table 2 indicate a role for prior risk beliefs and risk information.[7] The first behavioral risk perception parameter is the relative weight γ'_j placed on the worker's prior risk beliefs. For the pooled results, this estimate is not

[6] The results we found with this formulation were consistent with those found with an unrestricted functional form based on a second-order Taylor's series expansion. Karni (1985) provides a more general discussion of state-dependent utilities.

[7] For discussion of nonlinear estimation more generally, see Gallant (1975, 1986).

Table 2 Nonlinear least squares estimates of workers' reservation wage equation parameter estimates

	Pooled Sample	Chemical 1: Choroaceto-phenone	Chemical 2: Asbestos	Chemical 3: TNT
Perception Parameters				
Prior Information Weight γ_j'	0.880*	0.925*	0.899*	0.986*
	(0.112)	(0.149)	(0.181)	(0.242)
Weighted Implied Chemical Risk $\xi_1' s_1$	0.059*	−0.025	—	—
	(0.024)	(0.055)		
Weighted Implied Chemical Risk $\xi_2' s_2$	0.210*	—	0.189*	—
	(0.064)		(0.010)	
Weighted Implied Chemical Risk $\xi_3' s_3$	0.148*	—	—	0.154
	(0.049)			(0.101)
Utility Parameters				
Utility Constant ν_0	1.492*	0.524	1.538*	1.528*
	(0.207)	(0.654)	(0.378)	(0.448)
Utility Education Parameter ν_{Ed}	−0.022*	0.012	−0.022	−0.019*
	(0.008)	(0.019)	(0.014)	(0.006)
Utility Tenure Parameter ν_{Ten}	−0.006*	0.004	−0.007	−0.006
	(0.003)	(0.004)	(0.005)	(0.005)
Mean Utility Parameter[a] ν	1.132*	0.711**	1.134*	1.115*
	(0.070)	(0.370)	(0.112)	(0.140)
R^2	0.478	0.247	0.307	0.304

Asymptotic standard errors reported in parentheses.
*Asterisks indicate statistical significance at the 0.95 level (*) and the 0.90 level (**), two-tailed test.
[a]Utility function parameter evaluated at sample mean for education and tenure.

statistically different from 1.0. The value of γ_j' is 0.88, showing that workers assign a fractional weight of 0.88 to their prior beliefs and 0.12 to the hazard warning risk. The set of $\xi_j' s_j$ coefficients reflect the additional increment to the prior beliefs that arises from the joint influence of the relative weight ξ_j' on the warning information and the risk s_j implied by the warnings. These values range from 0.059 to 0.210, but again, with large standard errors.

We can use these estimates for γ_j' and ξ_j' to determine the implied values s_j that respondents attached to the different warnings. Doing so assumes that the same relative informational weight is applied to each warning, since γ_j' and ξ_j' did not vary with chemical j for the pooled results. The implied value of s_1 for chemical 1 is 0.49, the implied value for s_2 is 1.75, and the implied value of s_3 is 1.23. Thus, for two of the three chemicals, the worker acts as if the risk value implied by the hazard warning exceeds 1.0, which clearly is a behavioral anomaly. Note, however, that the empirical procedure only yielded estimates of the combined value $\xi_j s_j$, and the value of ξ_j was constrained to be the same across all chemicals. To trace the source of this apparent violation of the properties of probabilities, it must be the case that either the fractional informational content parameters sum to a value greater than 1.0, or the probability implied by the risk warning exceeds 1.0.

The chemical-specific estimates in the final three columns of Table 2 relax the assumption that γ'_j and ξ'_j are identical across chemicals. Many of the chemical-specific results are not statistically significant, perhaps in part because the chemical did not lead to much heterogeneity in the within-chemical results, so that there is a narrow range of compensating differential responses. In every instance, the γ'_j terms are statistically significant and in the range from 0.90 to 0.99, which is at or above the pooled estimates. The estimates for the three $\xi'_j s_j$ terms are less precise. The coefficient estimate for chemical 1 (chloroacetophenone), which is the least dangerous chemical, is less than half the size of its standard error. The chemical 2 (asbestos) results are much stronger. The coefficient estimate of 0.189 for $\xi'_2 s_2$, in conjunction with the estimate of γ'_2 of 0.899, yield an implied value of s_2 of 1.87, which is well above 1.0. Similarly, the point estimate for s_3 is even higher, because γ'_3 is almost 1.0, implying that ξ'_3 is very small. As a consequence, the behavioral probabilities are clearly not well behaved and do not accord with the basic properties of a probability measure.

The utility function parameters are of interest in ascertaining whether job injuries do in fact reduce the marginal utility of income in the post-injury state relative to the good health state. In terms of the model, evidence in support of this hypothesis is that ν should exceed 1.0 when estimated at the mean parameter values. The pooled sample results yield an implied utility function parameter 1.132 that is not significantly different from the 1.082 value estimated in Viscusi and Evans (1990), using the pooled sample results with a model in which we assumed that $q_j = z_j$.[8] Thus, the utility function estimates appear to be robust with respect to different specifications of the perception relationship.

The utility parameter estimates reported in the bottom panel of Table 2 distinguish the role of different worker characteristics that influence the structure of utility functions. The parameter ν distinguishes the good health state and post-injury state. For all statistically significant coefficients reported in Table 2, both more education and greater years of job experience decrease the utility weight ν. These variables may reflect the likely lower severity of job injuries for these classes of workers, thus reducing the spread between the utility function for good health and the utility function post-injury.

3. Behavioral versus subjectively-assessed probabilities

The results in Table 2 can be used to estimate the value of q_j implied by workers' expressed reservation wages for the post-labeling job. How do these values relate to the subjectively-assessed probabilities z_j that respondents reported for these post-labeling jobs? Did the risk levels implied by respondents' behavior coincide with the risk values that they indicated as pertaining to their jobs? This relationship will be explored using a simple linear equation relating q_j and z_j, where the constant term will equal zero and the coefficient of z_j will equal one if assessed and revealed probabilities are identical. Neither of these conditions holds, as the estimates (standard errors) for this simple bivariate regression are:

$$q_j = 0.128\,(0.014) + 0.362\,(0.051) z_j, \quad R^2 = 0.171.$$

These results indicate that the behavioral probability in effect compresses the stated probability. There is a floor of 0.13 on the behavioral probability even if the assessed probability is zero. Because the assessed probabilities reflect the net effects of all individual risk knowledge,

[8] See column 5, Table 4 of Viscusi and Evans (1990).

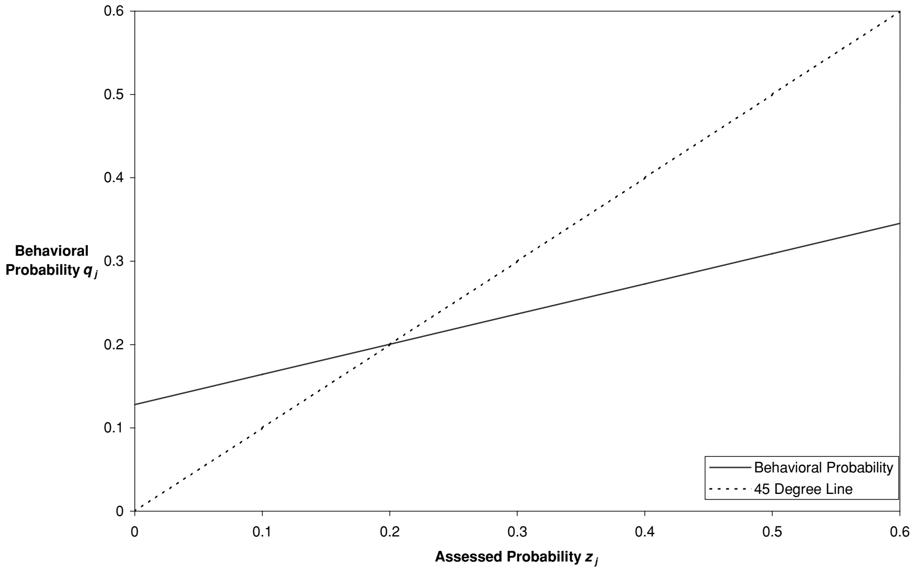

Fig. 1 Relationship between behavioral and assessed probabilities

this relationship is not simply attributable to prior beliefs or some other aspect of perceptions that is encompassed in a standard Bayesian framework. Risky job choices will always reflect some apparent risk belief even when the reported assessed risks are zero. At the upper end, there is a ceiling on probabilities q_j that cannot exceed 0.49 even if the reported assessed probability is 1.0. Note that this apparent ceiling is for the overall behavioral probability q_j, whereas the component hazard warning probabilities s_j often greatly exceeded 0.49.

Figure 1 sketches the implied relationships between q_j and z_j. There is a probability compression effect as small probabilities are boosted and larger probabilities are depressed. At $z_j = 0.20$, the relationship between subjective risk assessments and behavioral probabilities is identical, or $q_j = z_j$. Behavioral probabilities exceed assessed probabilities below this value, and are below assessed probability amounts above this value.

These findings suggest that behavior shifts resulting from the increased risk associated with hazard warnings are more muted than the risk levels that respondents associate with the warnings would indicate. Behavioral probabilities and assessed probabilities are particularly likely to diverge when the assessed probabilities are substantially different than the crossover point of 0.2 in Figure 1.

Although these findings resemble some perceptional bias patterns in the literature, they are substantively different. The well-known result first shown by Lichtenstein et al. (1978) and subsequently incorporated into Kahneman and Tversky's (1979) prospect theory and other models, is that assessed risks will be greater than actual objective risk levels for small risks and will be smaller for large risks.[9] In contrast, our model focuses on how the behavioral risk implicit in individual decisions relates to the reported or stated risk in the survey.

Table 3 summarizes the implications of these perceptional biases for the increased income the workers require to accept a greater risk. The required additional compensation levels for the three chemicals based on workers' stated risk beliefs appear in the first column of data

[9] For a review and recent evidence, see Hakes and Viscusi (2004). Also see Fischhoff et al. (1981).

Table 3 Impact of perceptional bias on survey responses for the chemical workers data set[a]

Warning Label	Predicted Median Percentage Increase in Compensating Differential for New Chemical Risk	
	Stated Probability Estimates	Behavioral Probability Estimates
Chemical 1: Chloroacetophenone	11.0	4.0
Chemical 2: Asbestos	20.3	18.0
Chemical 3: TNT	29.1	26.7

[a]Using parameter estimates from column 1 of Table 2, we generated for each worker predicted values for δ_j in Equation 9. In column 1 of this table, we assume perceptions are accurate and the probability is the true risk level. In column 2, we assume the behavioral probability is generated according to the perception in Equation 3 in the text.

in Table 3. These amounts range from 11 percentage points to 29 percentage points. The final column of statistics indicates the percentage wage increase that workers would require based on estimates that account for the behavioral probabilities and the utility function structure given these probabilities. These amounts are consistently lower than the reported wage increase amounts, with the greatest discrepancy being 7 percentage points for chemical 1.

The implicit value of a statistical injury is the ratio of the compensation increase demanded divided by the change in the risk. The effect of these behavioral probabilities on the implicit value of an injury is not as great as the effect on the amount of compensation demanded, because the effects on wage changes and behavioral risk levels are partially offsetting. For chemical 1, the implicit value of a job injury decreases from \$14,118 to \$13,680 after adjusting for behavioral probabilities; for chemical 2, the implicit value of an injury decreases from \$18,081 to \$18,077 after adjusting for behavioral probabilities; and for chemical 3, the implicit value of an injury increases from \$18,581 to \$18,688 after adjusting for behavioral probabilities. So although the components of this calculation—the perceived change in the risk and the compensation demanded—are more sensitive to the influence of the perceptional effects, they appear to influence the numerator and denominator proportionally, which does not appreciably change the estimates from those implied by posterior risk probabilities.

4. Implications

This paper's principal empirical innovation is jointly estimating the behavioral probabilities and utility functions revealed in decision contexts in which people equate their expected utility for two or more situations. The contexts considered focused on job risks, but the results have general applicability. Our estimation procedure yields estimates of the structure of utility functions as well as the behavioral probabilities implicit in these risky decisions.

The substantive dividend of this approach is that it enables one to distinguish the role of behavioral perceptional biases from apparent violations of the expected utility model. As shown in Viscusi (1989), stated probabilities in an experimental context may not correspond to perceived probabilities as assessed by respondents. Moreover, the probability values revealed through individual behavior are not the same as those reported by respondents, so that these reported amounts also should not be taken at face value.

Whereas reported probabilities were well behaved, these behavioral probabilities often were not. There is an apparent floor and ceiling on overall behavioral probabilities. These values increase less than proportionally with either the stated or assessed probabilities, with the result being that probabilities that should sum to 1.0 tend to be below 1.0. This pattern is not unprecedented. There is, for example, a well-established empirical relationship between individuals' assessed risks and objective measures of the risk that follows a pattern similar to that in Figure 1. The difference between the findings in the literature and those reported here is that it is the behavioral probabilities that are the matter of inquiry, and it is the bias in these risk values in relation to reported risk beliefs that we have examined.

There is evidence of an anomaly in risk beliefs with respect to the implicit perceived risks associated with the hazard warnings which, in conjunction with individuals' prior risk assessments, generate the post-warning risk assessment. These probability values often exceeded 1.0, indicating the inordinate implicit weight that participants attached to the experimental information.

Matters were more favorable for the utility function estimates. These values accorded with the hypothesized theoretical relationship in which serious job injuries should reduce the marginal utility of income. A major advantage of our approach is that the utility function estimates were obtained jointly with the behavioral probabilities, making it possible to distinguish the respect role of the structure of individual preferences and behavioral risk beliefs.

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