

**INDIVIDUAL DIFFERENCES IN
SUBJECTIVE RISK THRESHOLDS**

by

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Individual Differences in Subjective Risk Thresholds

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Abstract

Subjective risk perceptions are often encoded as responses to 0-1 questions in surveys or other qualitative risk scales. However, reference points for assessing an activity as risky are confounded by various characteristics of the respondents. This paper uses a sample of workers for whom quantitative risk assessments as well as dichotomous risk perception responses are available. It is shown that, given a quantitative risk measure, the thresholds for assessing an activity as risky vary systematically, particularly by education. The differences in such thresholds across worker groups are estimated. The resulting implications of using qualitative risk variables for assessing wage-risk tradeoffs are estimated, yielding results which are also relevant for many other areas involving similar qualitative variables.

KEY WORDS: RISK PERCEPTIONS; RISK THRESHOLDS; RISK PREMIUMS; DICHOTOMOUS VARIABLES.

1. Introduction

Studies of risk perceptions often use questions that obtain qualitative characterizations of risk levels. Surveys of worker risk beliefs, for example, inquire whether the worker is exposed to dangerous or unhealthy conditions.¹ Similarly, the U.S. Government frequently runs surveys that ask respondents to rate hazards in terms of whether or not they are truly very dangerous threats to individual health. Much of the research on cigarette smoking risk perceptions is of that character, as is research dealing with assessment of the risks of alcohol and other personal activities.² For example, one major government survey inquired whether the respondent believed that the "product is somewhat/very harmful." Asking whether a respondent perceives an activity as being risky or dangerous in some manner is possibly more the norm than is eliciting quantitative risk perception information.³

¹ This wording is, for example, included in the University of Michigan Survey of Working Conditions and the Quality of Employment Survey.

² See, for example, the U.S. Bureau of Alcohol, Tobacco, and Firearms (1988). See also the U.S. Department of Health and Human Services (1989).

³ There are, however, exceptions. See, for example, Kunreuther et al. (1978) in which respondents are presented with a quantitative risk scale based on individual longevity. Relative risk ratings are also frequently employed. See Fischhoff, et al. (1981).

A difficulty arises as to what the risk rating means if the threshold for assessing some activity as being risky differs across groups of respondents.⁴ This paper focuses on workers who have potentially hazardous jobs, but the issue is quite general. Do smokers have a different threshold for what they consider risky as compared to nonsmokers? Do people who have chosen to live near toxic waste dumps or nuclear power plants similarly have different ways in which they would characterize the riskiness of their exposures? The issue here is not the familiar one of valuation or quantitative risk assessment. It may be, for example, that workers on hazardous jobs place a lower value on their health and also underestimate the quantitative magnitude of the risks. Neither of these concerns is the issue here. Rather, it is whether for any particular value of a quantitative risk assessment they are more likely to assess their job as being hazardous or risky when given a qualitative question of that type. In particular, are there different scales that people use in triggering the response that some danger or risk is being encountered?

From an empirical standpoint, these responses are coded in 0-1 terms. If an activity is perceived as being risky, then it receives a value of 1; if not, it receives a value of 0. This is a

⁴ Concern with the definition, perception, and assessment of risk is of consequence for assessing the rationality of private decisions as well as the structuring of government interventions. See Kunreuther (1976), Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978), Machina (1987), Lichtenstein, Fischhoff, and Phillips (1982), and Fischhoff, Watson, and Hope (1984). For more general reviews, see Kahneman, Slovic, and Tversky (1982) and Hogarth (1990).

legitimate quantitative metric for scoring risk perceptions. However, comparisons across different groups of people will only be pertinent if they have a comparable reference point for assessing the presence of a risk. If, for example, college-educated respondents designate an activity as risky when the probability of the hazard is modest, whereas those without a college education designate an activity as risky only once a much higher probability of the adverse outcome is reached, then comparisons across these two groups based on subjectively coded risk variables will tend to overstate the risk levels of populations who have lower risk thresholds.

This paper seeks to ascertain whether there are in fact differences in such risk thresholds; whether these differences vary systematically with respondent characteristics; and whether such variations are of empirical consequence. Section 2 demonstrates how, for a sample of worker risk perceptions, the threshold levels for assessing the presence of a hazard vary systematically in expected ways. Data from the same sample for both quantitative risk assessments and the discrete risk perception variables provide an insight into the differences in risk thresholds. Section 3 explicitly estimates the critical cutoff values of the quantitative risk level used by different groups before designating a job as dangerous. The subjective risk estimates are then adjusted in Section 4 to obtain normalized values of the discrete danger perception that would occur if all respondents had the same critical quantitative risk level before designating a job as being dangerous. Section 5 explores the empirical implications of this phenomenon within the context of assessing wage-risk tradeoffs. The differences are not simply of random

measurement error, and the normalized danger perception variable performs much more similarly to the manner of the quantitatively scored variable. Section 6 concludes the paper.

2. Systematic Differences in Thresholds

The sample in this study consists of over 300 workers exposed to hazardous chemicals. This sample of workers, at four different chemical plants, consisted of both blue-collar workers as well as white-collar workers with substantial chemical exposures, such as research chemists.⁵ The distinctive feature of this data set is that it included two sets of risk questions pertaining to the worker's current job. The first question presented a linear risk scale in which the individuals were asked to indicate the level of their risk, where the anchor given was the average U.S. industry nonfatal injury risk. This variable is designated by *RISK*. The metric for this scale was the U.S. Bureau of Labor Statistics injury rate for industry, and respondents provided the equivalent risk level that they thought corresponded to the risk posed by their job.

Figure 1 illustrates a beta distribution fitted to the different values of *RISK*, in the full sample. Beta distributions are used often to approximate information regarding a variable with possible values between 0 and 1. A beta density is of the form

$$f_{\beta}(r|a,b) = r^{a-1}(1-r)^{b-1} / B(a,b), \quad (1)$$

⁵ This data set is drawn from the survey by Viscusi and O'Connor (1984).

where $B(a, b) = \Gamma(a) \Gamma(b) / \Gamma(a + b)$, with a and $b > 0$. The beta density in Figure 1 has parameters $a = 1.89$ and $b = 17.95$, implying a mean of 0.095 and a standard deviation of 0.064 which are identical to those for the variable *RISK* in the sample. Moreover, the various fractiles of this beta distribution are close to those for *RISK* in the sample. For example, for this beta distribution, the 0.25 fractile is 0.05 and the 0.75 fractile is 0.13 which are exactly equal to those observed in the sample.

As can be seen, the greatest density of the distribution is at a risk value below 0.10. This skewed distribution has a relatively long upper tail, which reflects the fact that most jobs do not pose a certainty of risk but rather involve risks that tend to be relatively rare events with a low probability. Since the risk involved is that of nonfatal job injuries, the probability is much higher than it would be if, for example, the risk pertained to fatalities.

The respondents also answered a qualitative risk question in which they were asked whether their job exposed them to dangerous or unhealthy working conditions. The specific wording of the question was: "Does your job at any time expose you to what you feel are physical dangers or unhealthy conditions?" This 0-1 question provided an indication of whether, on an overall basis, they considered their job as risky, thus making it possible to compare the results of this study with other worker surveys.⁶

⁶ In particular, a very similar wording of the risk belief question was used in the University of Michigan Survey of Working Conditions.

If individuals have the same cutoff levels for job risks that they consider to be risky, then the 0-1 danger perception variable suppresses some of the continuous aspects of the quantitative risk perception variable, but should strongly parallel it. Let c denote the cutoff quantitative *RISK* value at which the respondent considers the job to be dangerous. In particular, the null hypothesis is that if individuals have the same cutoff level c for what they would designate as being dangerous, then once their assessment on the BLS risk scale hits that critical level, they will score the risk as being present, leading to a coding of the danger perception variable equal to 1. The alternative hypothesis is that different worker groups have quite different values of c for which they consider the jobs to be dangerous, thus contaminating the implication of the discrete danger perception variable.

Table 1 presents the proportion of the sample for whom the subjective danger assessment value designated by *DANGER* equals 1. Column one indicates the value of the quantitative risk measure range. For example, the first category consists of all workers who scored the job risk on the BLS probability index scale as being between 0 and 0.05. The subsequent columns give the proportion of each sample group who consider their jobs as dangerous (*DANGER*=1) for each of the risk range rows.

The first column of Table 1 consequently gives the annual equivalent accident risk probability that the worker believes is comparable to the risk of his or her own job. The risk perception levels of workers appeared to be reasonable.⁷

The second column of Table 1 indicates the fraction of workers in each perceived objective risk index who view their job as exposing them to dangerous or unhealthy conditions. The focal point of this paper is how this 0-1 subjective perception variable, *DANGER*, correlates with the continuous risk measure. As can be seen from column 2 of Table 1, the fraction of workers who view their job as dangerous increases reasonably steadily with the risk level, and all workers who assess the annual injury frequency rate as being 0.21 or higher designate their job as dangerous.

There appear, however, to be some important differences across groups in the objective risk measures that trigger the *DANGER* designation. Comparison of columns 3 and 4 of Table 1 indicates that for every risk level category smaller than 0.21, college-educated workers are more

⁷For example, after being shown a hazard warning for the chemical sodium bicarbonate (i.e., household baking soda) which they were told would replace the chemicals with which they now worked, the workers assessed their risk as being 0.06, which is exactly equal to the accident risk (i.e., injury rate excluding illnesses) in the chemical industry. The perceptions here pertain to their prior risk beliefs before being shown any hazard warning label. Thus, this aspect of the results as well as the estimated compensating differentials associated with the sample are consistent with the quantitative risk perceptions being in a reasonable range.

likely to view their jobs as risky than those who are not college-educated. These discrepancies are particularly great at low risk levels, where college-educated workers are almost 3 times as likely as those who are not college-educated to view a job with a risk of 0-0.05 as hazardous.

The comparisons of white-collar and blue-collar workers in the final two columns of Table 1 have similar implications. The relative differences in the risk beliefs are, however, less stark than the differences by education group, as white-collar workers in the lowest risk range are just over twice as likely as blue-collar workers to view their jobs as risky.

An additional perspective on these beliefs is to use as a summary quantitative risk index whether the continuous *RISK* variable is above the average industry risk of 0.1, where the dichotomous variable *HRISK* (0-1 dummy variable) designates whether the worker's quantitative risk belief is a high risk job above the average injury and illness frequency rate in the industry. Table 2 summarizes the cross tabulations of *HRISK* and *DANGER* for the five sample breakdowns. For the full sample, 36 percent believe that their jobs pose an above average risk. Of these workers for whom *HRISK*=1, approximately four-fifths view their jobs as dangerous. If the objective risk score is below or equal to the industry average, the majority of workers do not view their job as risky.

The comparable patterns in Table 2 by educational status reflect the differing apparent thresholds for considering a job risky. For college-educated workers, even if *HRISK* has a value of zero more than half of all respondents call their jobs dangerous. Four-fifths of college-educated workers in above average risk jobs consider their positions dangerous. Workers who

are not college-educated display a fairly similar pattern of responses if their jobs are below average in risk, and are much less likely to view their job as dangerous if $HRISK$ equals 1. The white-collar/blue-collar split is similar but more muted, with white-collar workers being more likely to designate their jobs as dangerous if the objective risk measure is below the industry average.

3. Estimation of Risk Thresholds

The two sets of breakdowns of *DANGER* perceptions versus categorizations of the objective risk measure suggest that the quantitative risk threshold that must be reached before designating a job as dangerous varies systematically with the worker population group. In this section, we explicitly estimate the implicit risk threshold levels that underlie the worker responses.

More specifically, we estimate the different values of c , the different values of the cutoff for *RISK*, for each of the worker groups. Let a beta density function $f_{\beta}(r|a,b)$ represent the distribution of *RISK* values in each of the worker groups. For workers in Group i ($i=1,2,\dots,k$), let c_i denote the critical value of the continuous risk measure that must be attained before designating a job as dangerous. So, if a worker in Group i has a *RISK* value above c_i then that worker designates his/her job as dangerous ($DANGER = 1$), and designates his/her job as not dangerous ($DANGER = 0$) otherwise. Then the proportion of the workers in Group i with $DANGER = 1$ is

$$p_i = 1 - I_{c_i}(a, b) \quad \text{and} \quad (2)$$

$$1 - p_i = I_{c_i}(a, b) \quad (3)$$

is the proportion of the workers in Group i with $DANGER = 0$, where

$$I_{c_i}(a, b) = \int_0^{c_i} f_{\beta}(r|a, b) dr \quad (4)$$

is an incomplete beta function. Hence, for Group i, the marginal probability that a worker is recorded with $DANGER = 1$ is p_i and the marginal probability that a worker is recorded with $DANGER = 0$ is $1 - p_i$. Now, suppose that in a random sample of n_i workers from Group i, r_i are recorded with $DANGER = 1$ and the remaining $n_i - r_i$ with $DANGER = 0$. The likelihood function is therefore

$$l(r_1, r_2, \dots, r_k | n_1, n_2, \dots, n_k, p_1, p_2, \dots, p_k) = \prod_{i=1}^k \binom{n_i}{r_i} p_i^{r_i} (1 - p_i)^{n_i - r_i} . \quad (5)$$

Then the maximum likelihood estimate of p_i is $\hat{p}_i = r_i / n_i$. Then it follows from (2) that the maximum likelihood estimate of $I_{c_i}(a, b)$ is

$$\hat{I}_{c_i}(a,b) = 1 - \hat{p}_i = 1 - r_i / n_i. \quad (6)$$

Further, since $I_{c_i}(a,b)$ is increasing in c_i , the maximum likelihood estimate for c_i is \hat{c}_i for which

$$I_{\hat{c}_i}(a,b) = \hat{I}_{c_i}(a,b) = 1 - r_i / n_i. \quad (7)$$

Given values of a , b , n_i , and r_i , the values of \hat{c}_i can be determined easily from tables on the incomplete beta function (for example, extensive tables can be found in Pearson (1934, 1968)) or can be computed using the beta inverse function in statistical software such as SAS.

Using the beta density function estimated in Section 2, and shown in Figure 1, for the variable RISK and given the sample results for the DANGER variable, the resulting values of \hat{c}_i by sample group are shown in Table 3. These estimates clearly indicate that the white-collar/blue-collar difference is due entirely to differences in education. Within educational groups, the blue-collar values of \hat{c}_i are almost identical to the full sample estimates and only marginally different from the white-collar values.

College, however, plays a pivotal role. Workers who have completed college view a job with an accident frequency rate of 0.055 or greater as being a dangerous job, whereas workers

who did not complete college have a \hat{c}_i value of 0.087, which is 0.032 greater, indicating that those who are not college-educated have a greater tolerance for risk. For the full sample, the \hat{c}_i value is 0.071.

That college-educated workers should view their jobs as risky is quite reasonable since the research chemists in the sample are, in fact, exposed to chemical hazards. What is most striking is that their characterization of risk is quite different. A much lower risk level will trigger a positive response on their part to a qualitative question of whether their job was dangerous.

The most reasonable explanation is that a difference in their valuation of risk has created a difference in subjective risk judgments.⁸ College-educated workers have higher current income levels and higher lifetime wealth levels, which will raise their valuation of health status. Indeed, for this sample the income elasticity of the implicit value of job injuries is 1.0.⁹ Because of the linkage between job risks and income, this study has focused on the influence of exogenous education characteristics on the c_i values.

An alternative hypothesis might be that the different c_i values reflect better risk information for college-educated workers. However, if this were the case, then the *RISK* values

⁸ For further analysis of the role of risk attitudes, valuations, and heterogeneity in influencing risk taking behavior, see MacCrimmon and Wehrung (1990) and Slovic and Lichtenstein (1968).

⁹ See Viscusi and Evans (1990) for these results.

would be influenced as well. The test here is not whether college-educated workers are more likely to be aware of job risks but whether they are more likely to designate a job as dangerous if their continuous *RISK* score reaches a particular level. If college workers are more aware of risks, there is no reason to expect differential awareness that would disproportionately affect the dichotomous risk measure. In contrast, differences in valuations of risk by educational group will create a greater expected welfare loss for the college-educated from any given value of *RISK*, thus accounting for the observed discrepancy in c_i levels.

4. Normalization of Subjective Danger Thresholds

For the dichotomous *DANGER* variable to be a valid risk measure for comparisons across workers, the cutoff value of *RISK* should be standardized across worker groups. Let the critical value of *RISK* for designating a job as risky be the estimated c_i for the full sample, 0.071.

Table 4 recomputes the value of *DANGER* with this normalized cutoff value, where we designate these normalized values by *DANGER_I*. Mean values of *DANGER* for the sample group appear in each cell of Table 4, and the counterpart values of *DANGER_I* are in parentheses below them. The changes in the danger perceptions are greatest for workers who are not college-educated. With the standardized risk cutoff value, the fraction of workers who view their jobs as dangerous jumps from 0.48 to 0.84 for white-collar workers and from 0.46 to 0.65 for blue-collar workers. For the college-educated the normalization reduces the fraction with

danger perceptions from 0.69 to 0.59 for white-collar workers and from 0.70 to 0.67 for blue-collar workers.

Perhaps the shifts of greatest significance are that normalized risk cutoffs restore the two broad risk relationships that unexpectedly did not hold without normalization. Danger assessments for blue-collar workers now exceed those of white-collar workers (0.65 versus 0.63), whereas the reverse was true before. College-educated workers now have a lower mean value of *DANGER* than workers who are not college-educated (0.61 versus 0.67), whereas their unadjusted *DANGER* value was almost one and a half times the size of that of workers who are not college-educated. The aberrational values of *DANGER* become reversed after accounting for the different danger cutoff values.

5. Effect of Danger Normalization on Estimated Wage-Risk Tradeoffs

The effect of differing risk thresholds on the statistical properties of the *DANGER* variables is not innocuous. Consider the influence of the differing c_i values on the value of the estimated wage-risk tradeoff. In particular, consider a standard wage equation of the form

$$EARNINGS = \alpha + \beta_1 DANGER + \sum_{i=2}^n \beta_i X_i + \varepsilon , \quad (8)$$

where α is the constant term, the β_i 's are coefficients, the X_i 's are a series of explanatory variables, and e is a random error term. If *DANGER* is subject to random measurement error,

then the coefficient of *DANGER* will be biased downward. This is the standard errors-in-variables result in econometrics.¹⁰

As the starting point for analysis consider the estimated *EARNINGS* equation in column 1 of Table 5, where the other variables pertain to worker age (0-1 dummy variable (d.v.) *AGE30-49*), race (0-1 d.v. *BLACK*), sex (0-1 d.v. *MALE*), marital status (0-1 d.v. *MARRIED*), college graduate (0-1 d.v. *COLLEGE*), and worker experience (*EXPERIENCE*, in years). The estimated coefficient of *DANGER* is \$2,034, which, given a mean value of *DANGER* of 0.50, implies an annual value of compensation for risk equal to \$1,017.

Consider the results if we replace *DANGER* by *DANGER1* in the equation, thus eliminating the role of different risk cutoff values. The results in column 2 of Table 5 indicate that the risk premium is cut almost in half -- to \$1,140 -- if the job is viewed as dangerous. This reduction in the value of the estimated coefficient is the opposite of what one would predict if the measurement error were random. Coupled with the mean value of *DANGER1* equal to 0.65, this result implies an annual compensation value for risk of \$740.

As a check on the appropriate level of compensation, the third column of Table 5 presents estimates for which the job risk variable is the continuous *RISK* measure. The coefficient of 7158 and the mean value of *RISK* of 0.095 imply annual wage premiums for risk of \$680, which is extremely close to the \$740 value obtained with *DANGER1*. Thus, the danger

¹⁰See, for example, Greene (1990), especially pp. 294-295.

perceptions corrected for differences in risk cutoffs yield estimated risk premiums much closer to those obtained with a quantitative continuous risk index.

These assessments have two principal implications. First, the errors caused by differences in risk thresholds are not random. In this instance the result was to create an upward bias rather than the expected downward bias. Second, the normalized values generate empirical results much more similar in character to the estimates obtained using a continuous risk measure.

6. Conclusion

Qualitative variables commonly occur in research contexts. The variables often pertain to risk measures such as those considered here. However, a survey could similarly obtain many other types of information for which a difference in the underlying quantitative metric across individuals creates differences in the ways in which respondents assess the qualitative dichotomous variables.

This paper focused on perception of job hazards but it is likely that this phenomenon is also relevant to other types of risk perception. There were important differences among sample members in the quantitative risk level that triggered a stated awareness of the presence of risks. Differences across educational groups and worker types both appear to be consequential, but it was the educational group bias that was by far the greatest.

Because this study analyzed a survey in which information about the underlying quantitative risk assessment as well as the dichotomous qualitative risk awareness variable was

available, it was possible to estimate the differences in the risk thresholds across worker groups.

These cutoff values varied substantially, with college-educated workers being those with the lowest cutoff values. Annual injury frequency rates had to be 0.032 greater for respondents who were not college-educated to indicate that a job was dangerous.

The problems raised by these differences in risk thresholds are not innocuous. In particular, they do not fit the predicted pattern for random measurement error. Rather than creating a downward bias in the estimated wage-risk tradeoffs, this difference in thresholds led to a considerable upward bias.

These results reflect a more general phenomenon in which differences in risk valuation could contaminate responses to questions that purportedly deal only with risk perception. Although, ideally, respondents should think only of the probability when asked whether a job or activity is risky, whether they consider it to be dangerous depends also on whether they value the adverse health effects highly. Those with college education should be less willing to incur health risks because of their greater affluence, and this in turn appears to affect their expressed risk beliefs.

References

- Fischhoff, B., S. Lichtenstein, P. Slovic, S.L. Derby, R.L. Keeney, *Acceptable Risk*, Cambridge: Cambridge University Press, 1981.
- Fischhoff, B., S. Watson, and C. Hope, "Defining Risk," *Policy Sciences*, 17 (1984), 123-139.
- Greene, William H., *Econometric Analysis*, Second Ed., New York: Macmillan Publishing Co., 1990.
- Hogarth, R.M., ed., *Insights in Decision Making: A Tribute to Hillel J. Einhorn*, Chicago: University of Chicago Press, 1990.
- Kahneman, Daniel, Paul Slovic, and Amos Tversky, eds., *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, 1982.
- Kunreuther, Howard, "Limited Knowledge and Insurance Protection," *Public Policy*, 24:2 (1976), 227-261.
- Kunreuther, H., H. Ginsberg, L. Miller, P. Sagi, P. Slovic, B. Borkan, and N. Katz, *Disaster Insurance Protection: Public Policy Lessons*, New York: Wiley, 1978.
- Lichtenstein, S., B. Fischhoff, and L.D. Phillips, "Calibration of Probabilities: The State of the Art to 1980," in Daniel Kahneman, Paul Slovic, and Amos Tversky, eds., *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, 1982, pp. 306-334.

- Lichtenstein, S., P. Slovic, B. Fischhoff, M. Layman, and B. Combs, "Judged Frequency of Lethal Events," *Journal of Experimental Psychology: Human Learning and Memory*, 4 (1978), 551-578.
- Machina, M.J., "Decision Making in the Presence of Risk," *Science*, 23b (1987), 537-543.
- MacCrimmon, K.R. and D.A. Wehrung, "Characteristics of Risk Taking Executives," *Management Science*, 36 (1990), 422-435.
- Pearson, K., *Tables of the Incomplete Beta Function*, Cambridge: University Press, 1934, 1968.
- Slovic, P., and S. Lichtenstein, "The Relative Importance of Probabilities and Payoffs in Risk Taking," *Journal of Experimental Psychology Monograph Suppl.*, 78, Part 2 (1968).
- U.S. Bureau of Alcohol, Tobacco, and Firearms, *Final Report of the Research Study of Public Opinion Concerning Warning Labels on Containers of Alcoholic Beverages*, Vol. 1, Table 2, 1988 (December).
- U.S. Department of Health and Human Services, *Reducing the Health Consequences of Smoking: 25 Years of Progress*, A Report to the Surgeon General, Washington, D.C.: U.S. Government Printing Office, 1989.
- Viscusi, W. Kip and William Evans, "Utility Functions That Depend on Health Status: Estimates and Economic Implications," *American Economic Review*, 80:3 (1990), 353-374.
- Viscusi, W. Kip and Charles O'Connor, "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?," *American Economic Review*, 74 (1984), 942-956.

FIGURE 1
Beta Distribution Fitted to the Continuous Risk Measure

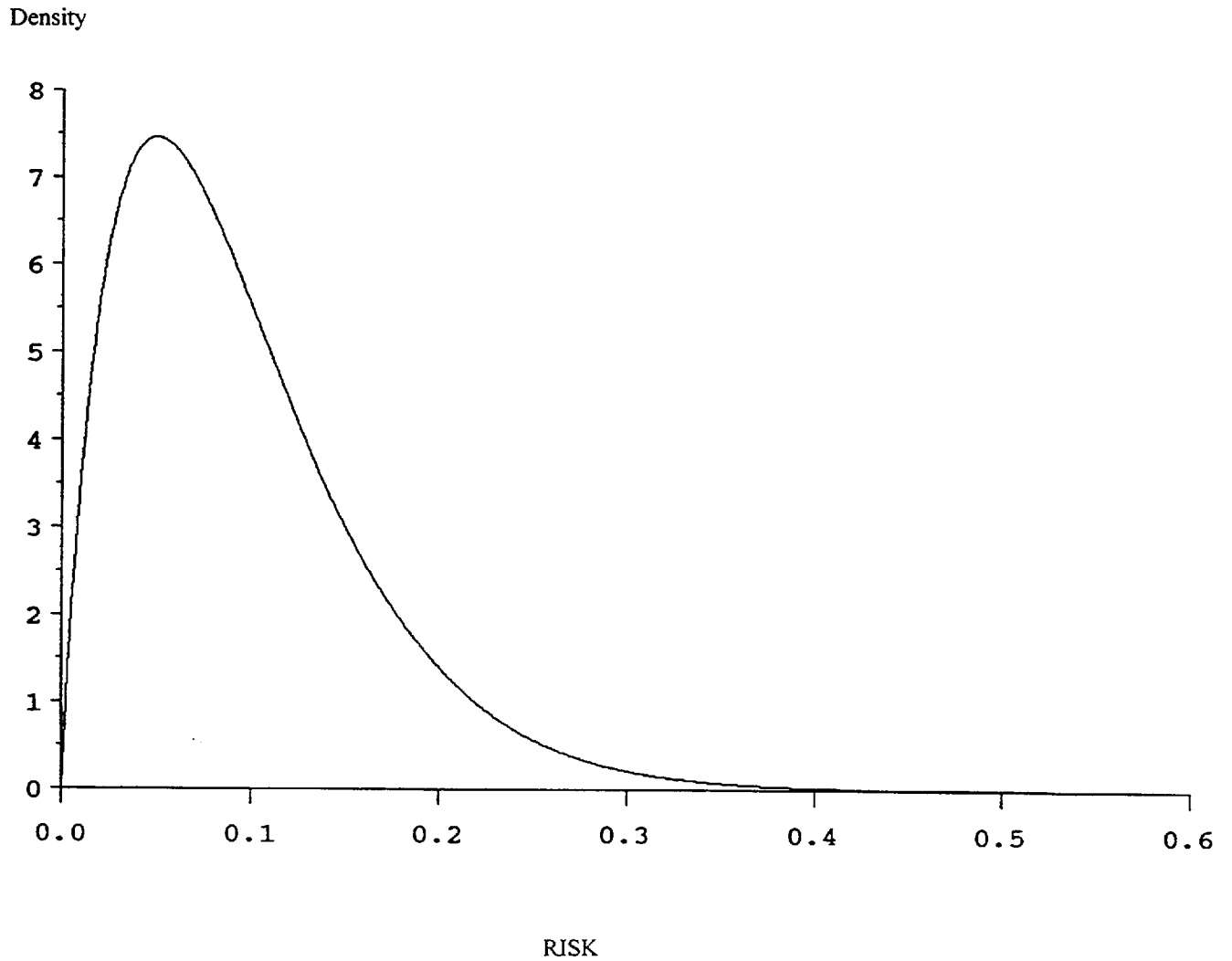


Table 1 : Proportion of Sample within Risk Category for whom DANGER=1

Risk Measure Range	Full Sample	College-Educated	Not College-Educated	White-Collar	Blue-Collar or Technical
0 - 0.05	0.33	0.50	0.19	0.47	0.23
0.06 - 0.10	0.52	0.68	0.40	0.58	0.46
0.11 - 0.15	0.79	0.83	0.76	0.80	0.78
0.16 - 0.20	0.75	0.76	0.73	0.88	0.65
0.21 - 0.25	1	1	1	1	1
0.26 - 0.30	1	1	1	1	1
0.31 - 0.35	1	1	1	1	1

TABLE 2: Relation of Danger Perceptions to Continuous Risk Assessments Above the Industry Average (Proportions of Sample by Category)

		DANGER		Total
		0	1	
HRISK	0	0.36	0.28	0.64
	1	0.07	0.29	0.36
Total		0.43	0.57	

Full Sample
n = 335

		DANGER		Total
		0	1	
HRISK	0	0.23	0.37	0.61*
	1	0.08	0.32	0.39*
Total		0.31	0.69	

College-Educated
n = 155

		DANGER		Total
		0	1	
HRISK	0	0.46	0.21	0.67
	1	0.07	0.26	0.33
Total		0.53	0.47	

Not College-Educated
n = 180

		DANGER		Total
		0	1	
HRISK	0	0.28	0.35	0.63
	1	0.07	0.31	0.37*
Total		0.35	0.65*	

White-Collar
n = 150

		DANGER		Total
		0	1	
HRISK	0	0.42	0.23	0.65
	1	0.08	0.27	0.35
Total		0.50	0.50	

Blue-Collar or Technical
n = 185

*Row/column does not add up due to rounding.

**TABLE 3: Estimated Cutoff Values of Continuous Risk Measure for DANGER = 1
(by Worker Group)**

	College-Educated	Not College-Educated	Full Sample
White Collar	0.055	0.085	0.060
Blue Collar or Technical	0.053	0.087	0.081
Full Sample	0.055	0.087	0.071

TABLE 4: Summary of Subjective Danger Assessments (and Danger Assessments if Identical Risk Cutoff Applies for the Full Sample) by Worker Group

Means of DANGER (and DANGER1)			
	College-Educated	Not College-Educated	Full Sample
White Collar	0.69 (0.59)	0.48 (0.84)	0.65 (0.63)
Blue Collar or Technical	0.70 (0.67)	0.46 (0.65)	0.50 (0.65)
Full Sample	0.69 (0.61)	0.47 (0.67)	0.57 (0.64)

**TABLE 5: Estimates of Earnings Equations with Subjective Danger Variable,
Standardized Danger Variable, and Continuous Risk Variable**

Dependent Variable: EARNINGS

Independent Variable	Coefficient (Standard Error)		Coefficient (Standard Error)		Coefficient (Standard Error)
INTERCEPT	10707* (526.24)		10910* (612.95)		11068* (611.24)
DANGER	2034.03* (407.55)	DANGER1	1139.62* (452.25)	RISK	7158.46* (3388.89)
MIDAGE	2339.09* (447.81)		2141.12* (467.36)		2102.81* (469.12)
BLACK	2218.84* (714.33)		2499.63* (746.76)		2264.73* (761.52)
MALE	1947.53* (411.64)		1946.81* (433.97)		1966.63* (436.20)
MARRIED	498.78 (445.46)		827.89 (477.46)		788.08 (479.87)
COLLEGE	1681.39* (555.16)		2105.21* (576.45)		1939.92* (583.40)
EXPER	86.39* (16.65)		78.33* (17.37)		78.35* (17.47)
R ²	0.46		0.40		0.40

* p-value < 0.05.