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A fundamental issue in the economics of uncertainty is how individuals process information and make choices under uncertainty.[1] In a recent analysis of the findings on risk perception, Kenneth Arrow (1982) concluded that the evidence regarding individual rationality was, at best, quite mixed. A prominent example of apparent irrationality of actual consumer behavior is that consumers, who presumably are risk averse, have failed to purchase heavily subsidized federal flood insurance.[2] In the case of the market for hazardous jobs, which is the focus of this study, Viscusi (1979) found that workers' risk perceptions were positively correlated with the industry risk and that workers who perceived job risks received compensating wage differentials.[3] Nevertheless, workers in high risk jobs displayed behavior consistent with an adaptive response in which workers accept jobs whose risks are not fully understood, learn about these risks based on their on-the-job experiences, and then quit if these experiences are sufficiently unfavorable given the wage for the job.

Although the positive injury rate-quit rate linkage is consistent with an adaptive response, there has been no study that has investigated the dynamics of this relationship. Do workers learn about risks on the job, and does this change in perceptions lead workers to revise their reservation wage rates in the expected manner? More fundamentally, even in the absence of such learning, do workers have subjective risk assessments that generate compensating differentials in the manner that is consistent with studies of risk premiums for hazardous occupations and industries? In this paper we will extend this line of research by analyzing the nature of workers' risk assessments, how workers process information, and how changes in risk perceptions affect their decisions.

Since no existing data sets provide information on the evolution of workers' risk perceptions, we undertook a sample survey in which we ascertained worker responses to labels of potentially hazardous chemicals. We chose this form of information because the chemical industry already has some experience in conveying this information in a manner that workers can understand, thus making it possible to analyze the learning process rather than focusing on the design of the format for the information. In addition, this type of risk information has substantial policy relevance since chemical labeling is the major component of the OSHA hazard communication policy. This $3 billion policy was the most expensive social regulation issued during the first three years of the Reagan Administration.[4]

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[1]A lucid discussion of the relationship of information to economic behavior is provided by Kenneth Arrow (1974).

[2]Howard Kunreuther's (1976) analysis of flood insurance stresses a lack of consumer information as an important factor. A major theme of this study is that workers also are acting within a context of highly imperfect information.

[3]Viscusi (1979) also linked compensating differentials to objective risk measures, yielding comparable wage premiums. Other studies in the compensating differentials literature include Richard Thaler and Sherwin Rosen (1976), Robert Smith (1976), and Charles Brown (1980). Smith (1979) and Viscusi (1983) provide critical surveys of this literature.

[4]The EPA pesticide and toxic chemical regulations also include chemical labeling as a policy option. See Susan Hadden (1983) for a review of the role of labeling policies of federal agencies.

In Section I we discuss the nature of the sample and present the empirical results for the situation before information provision to establish a reference point for subsequent results. These findings are also of interest in their own right because the survey provides extensive risk-related information that included detailed risk-assessment questions and information on whether workers would repeat their job choice. These data will consequently enable us to make a more direct link than in previous research between workers' risk perceptions and labor market outcomes, such as compensating differentials for risk. The effect of the chemical labels on workers' risk perceptions is the subject of Section II. We estimate both the risk level implied by the hazard warning and the informational content relative to the worker's prior beliefs. This evidence is consistent with a Bayesian learning process in which workers retain some influence of their priors and incorporate the new information in the expected manner. Section III's analysis of the effect of risk information on compensating differentials and worker turnover provides the first explicit test of the effect of changes in workers' risk perceptions on labor market performance.

The overall picture that emerges is that workers begin jobs with imperfect information, but there are many rational elements to worker behavior, and the extent of risk-related mismatches of jobs and workers is not rampant. After acquiring risk information, most workers display the capacity to update their probabilistic beliefs in a manner that is broadly consistent with Bayesian analysis. The adaptive responses that emerge suggest that workers are engaged in an ongoing experimentation process in which they learn about the risks posed by their job and quit once the position becomes sufficiently unattractive.

I. The Sample and Baseline Results

Since no existing body of data provides longitudinal information on workers' risk perceptions, we developed a survey to enable us to analyze worker responses to job hazard information. The focus of this section is on the nature of the sample and the empirical results for the situation before workers received risk information. Because of the more comprehensive nature of the risk questions, it is possible to broaden the empirical support for the principal labor market impacts of employment hazards.

The sample consisted of 335 employees in the chemical industry. During the first six months of 1982, the managers responsible for chemical labeling interviewed workers at four plant locations of three major chemical firms. The operations represented included research and development as well as manufacturing. The sample included a broad range of occupational groups exposed to chemicals. Engineers, technicians, chemists, mechanics, researchers, and supervisors were all included. Over half of the sample—187 workers—consisted of workers who were either on hourly pay or were technicians. This group, which we will denote by *BC/TECH*, closely parallels the blue-collar subsample analyzed in Viscusi (1979) and will be the focus of much of the empirical work in this section.

Table 1 summarizes the sample characteristics for the full sample and the *BC/TECH* subsample. The sample characteristics follow the pattern one would expect for a national chemical firm. The average worker age is 39, and the majority of all workers are white males (only 7 percent blacks and 43 percent females). The individuals averaged two years of college education, or years of schooling (*EDUC*) equal to 14. Almost two-thirds of the sample were married with an average of 1.36 children (*KIDS*). Their total work experience (*EXPER*) was 18 years, 8 of which were at the particular firm (*TENURE*). The average annual earnings (*EARNG*) was over $21,000.

The most distinctive characteristic of the sample was the inclusion of a series of risk perception questions. The *DANGER* variable pertains to whether or not the worker's job exposes him to dangerous or unhealthy conditions. The wording of this question parallels that in the University of Michigan *Survey of Working Conditions* (1975) used by Viscusi (1979) and will be used in assessing the comparability of the empirical results. In that study, 52 percent of the blue-collar workers viewed their jobs as dangerous. The

TABLE 1—SAMPLE CHARACTERISTICS: MEANS AND STANDARD DEVIATIONS

Variable	Full Sample	*BC/TECH* Subsample
AGE (in years)	38.8	38.9
	(11.8)	(12.8)
BLACK (0–1 race dummy variable (*dv*))[a]	0.07	0.10
MALE (0–1 sex *dv*)[a]	0.57	0.42
EDUC (years of schooling)	14.44	12.47
	(3.21)	(2.05)
MARRIED (0–1 marital *dv*)[a]	0.64	0.62
KIDS (number of children)	1.36	1.10
	(1.52)	(1.28)
EXPER (years of work experience)	18.38	19.19
	(11.68)	(13.0)
TENURE (years of experience at firm)	8.19	7.15
	(7.22)	(6.41)
EARNG (annual earnings)	$21,120.4	$15,768.6
	($8,332.1)	($3,596.6)
DANGER (0–1 risk *dv*)[a]	.57	0.50
RISK (scaled risk)	0.10	0.09
	(0.06)	(0.07)
HRISK (0–1 high risk *dv*)[a]	0.36	0.35
WPREM (0–1 perceived wage premium *dv*)	0.11	0.10
TAKEA (0–1 repeat job choice *dv*)[a]	0.79	0.77
TAKEB (0–1 repeat job choice *dv*)[a]	0.97	0.96
QUITA (0–1 quit intention *dv*)	0.12	0.12
QUITB (0–1 quit intention *dv*)	0.05	0.05
Sample Size	335	185

[a]Standard deviations for 0–1 dummy variables are omitted since they can be calculated from their fraction m in the sample, where the standard deviation is $(m - m^2)^{.5}$.

results here are quite similar, as 57 percent of the overall sample viewed their jobs as dangerous, with 50 percent of the *BC/TECH* subsample perceiving some risk.

Although the mean *DANGER* levels are not unexpected, the relative riskiness rankings are the opposite of what one might expect since the *BC/TECH* group presumably faces greater risks. Whether or not this is actually the case is not clearcut since the white-collar research chemists may in fact incur greater health risks than, for example, maintenance personnel. The more similar results for the continuous *RISK* variable discussed below suggest, however, that these results may not stem from an actual difference in riskiness. Rather, the *BC/TECH* workers may have a less stringent risk level cutoff for considering whether their jobs are hazardous. Since willingness to accept a risk is negatively related to one's wealth, it is not unexpected that higher-income workers are more likely to regard a job as dangerous, for any given risk level.[5]

Except in the case of one study using the *DANGER* variable, all previous analyses of risk premiums have used objective occupational or industry risk measures. For this paper we developed a variable that would reflect the worker's subjective assessment of the BLS injury and illness frequency rate for his job. From the standpoint of the theoretical foundations of the compensating differential theory, the wage-risk relationship should be driven by such subjective risk perceptions. Aggregative risk variables simply serve as an objective proxy for this variable.

To overcome the difficulties arising from different danger reference points and to provide a continuous risk measure that will make

[5]Educational differences and related differences in ability to perceive risks may also play a role.

possible a detailed analysis of worker learning, we developed a continuous *RISK* variable. We presented to each worker a linear scale, ranging from very safe to dangerous. To provide an objective reference point, an arrow marked the average U.S. private sector injury and illness rate. Each respondent marked on the scale the risk level that he assessed for his job. This variable was then converted into probabilistic terms, that is, scaled between 0 and 1, where risk is on a scale comparable to the BLS annual injury frequency rate. The mean *RISK* levels for the full sample and the *BC/TECH* subsample are comparable to the national average private sector risk probabilities and about 50 percent larger than the recent levels of the chemical industry's injury and illness frequency rate. This discrepancy is not unexpected since BLS statistics primarily capture safety-related accidents and underreport the long-term illnesses from chemical exposures; reported injury rates will understate the actual risk level.

Using the *RISK* responses, we also created a job hazard dummy variable similar to *DANGER* except that the risk threshold reference point was the same for all respondents. The high-risk variable *HRISK* assumed a value of 1 if the worker faced a risk above the U.S. average, and 0 otherwise. A third of the sample viewed their jobs as being high risk, and two-thirds viewed their jobs as being comparatively safe. In conjunction with the earlier *RISK* results, these findings suggest that the chemical industry's relatively good accident record may be a reasonable reflection of most workers' perceptions, but the presence of substantial health risks leads a sizable minority to consider their jobs particularly hazardous.

Since the time of Adam Smith, economists have observed that perceived risks will generate compensating wage differentials since workers will demand extra compensation for jobs that pose extra risk.[6] Table 2 summarizes the risk variable results for equations in which annual earnings (*EARNG*) and its natural logarithm (*LNEARNG*) serve as the dependent variables. Each equation also included an extensive group of variables that typically enter such earnings equations, such as the individual's education and work experience. For the *BC/TECH* subsample, the annual risk premium of \$700–\$800 for *DANGER* was of roughly the same magnitude as the \$900 annual compensation found for the blue-collar subsample in Viscusi (1979) for both *DANGER* and the BLS injury rate.

As with that study, the full sample results were not successful because of an inability to disentangle the wage premiums for risk from the positive overall relationship between job quality and individual income. The change in earnings equations in Section III will not be subject to this difficulty. Restricting the sample to males only eliminates some of the problems arising from failing to control adequately for the omitted variables that determine individual earnings. Male workers' jobs tend to involve more direct handling of chemicals, and the annual risk premiums are considerably larger than for the *BC/TECH* subsample.

Of the three risk variables, *DANGER* yielded the largest annual risk premiums. These were somewhat larger than those for *RISK*, which were about \$100 less. The above-average risk variable *HRISK* led to the smallest annual risk premiums, but the effects were consistently positive and statistically significant (at the 5 percent level, one-tailed test). This pattern may reflect the shortcomings of the *HRISK* variable, which may be a less accurate measure of the underlying job risk, thus leading to a downward bias in its coefficient. The general implications of these findings are less ambiguous. The consistently significant results using the subjective risk variables and the similarity in the *DANGER* and *RISK* premiums to those in earlier studies should bolster one's confidence in the validity of the compensating differential theory.

A closely related issue is whether workers are aware of any risk premiums. Since no previous study had asked workers whether they believed that they received a risk premium, we developed a variable *WPREM* that

[6]See fn. 3 above for a list of several previous risk premium studies.

TABLE 2—SUMMARY OF COMPENSATING DIFFERENTIAL RESULTS[a]

Dependent Variable	Sample	Risk Variable	Risk Coefficient	Average Annual Risk Premium
EARNG	*BC/TECH*	*DANGER*	1577.2 (438.1)	\$788.6
LNEARNG	*BC/TECH*	*DANGER*	0.097 (0.029)	\$746.5
EARNG	*BC/TECH*	*RISK*	6898.4 (3461.1)	\$636.2
LNEARNG	*BC/TECH*	*RISK*	0.479 (0.231)	\$665.3
EARNG	*BC/TECH*	*HRISK*	738.4 (465.5)	\$258.4
LNEARNG	*BC/TECH*	*HRISK*	0.053 (0.031)	\$289.8
EARNG	Full (males)	*DANGER*	2117.5 (775.6)	\$1385.7
LNEARNG	Full (males)	*DANGER*	0.124 (0.036)	\$1875.3
EARNG	Full (males)	*WPREM*	1583.1 (1179.9)	[b]
LNEARNG	Full (males)	*WPREM*	.1094 (.0549)	\$278.8
EARNG	Full	*DANGER*	169.03 (529.51)	[b]
LNEARNG	Full	*DANGER*	0.018 (0.025)	[b]

[a]Each equation also includes the following variables: *AGE*, *BLACK*, *MALE*, *EDUC*, *MARRIED*, *KIDS*, and *EXPER*. The full sample results also include a *BC/TECH* dummy variable. The standard errors are shown in parentheses below the coefficients.

[b]Annual risk premiums are not reported since the coefficients are not statistically significant (at the 5 percent level, one-tailed test).

assumed value of 1 if the worker believed that he received higher pay because of the nature of the chemical industry and 0 otherwise. This variable reflects compensating differentials for working in the chemical industry as opposed to some other industry, not risk premiums per se. Since two-thirds of the sample regarded their jobs as safer than the U.S. average, these incremental premiums should not be large. Only 10 percent of the sample believed they received such a chemical industry premium, and those that did earned an average wage premium of under \$300, controlling for other factors (see *LNEARNG* equation, Table 2). As expected, the probability that the worker perceives a risk premium is strongly and positively related to each of the three risk variables, as the logit results in Table 3 indicate.

Since over one-third of the sample believed that they faced above-average risks and only one-tenth acknowledge the existence of relative wage premiums, roughly one-quarter of the sample might appear to behave in a manner that is inconsistent with the standard theory. This need not be the case since workers may, for example, earn some form of economic rent that makes the job attractive despite the absence of a perceived relative risk premium. Moreover, since the overall risk premiums average under \$1,000 annually and only \$300 for the relative chemical industry differential, many respondents may not have believed that the risk premium they received was sufficiently large to make the chemical industry salary substantially different from what could be earned elsewhere.

Some portion of this group who perceive risks but not relative risk premiums may, however, be mismatched. On a conceptual basis, there clearly is some potential for some

TABLE 3—MAXIMUM-LIKELIHOOD ESTIMATES FOR PERCEIVED RISK PREMIUM AND TURNOVER EQUATION[a]

Dependent Variable	Risk Variable	Coefficient[b]
WPREM	*DANGER*	2.96 (0.75)
WPREM	*RISK*	6.89 (2.78)
WPREM	*HRISK*	0.54 (0.38)
TAKEA	*DANGER*	−1.42 (0.35)
TAKEA	*RISK*	−11.22 (2.32)
TAKEA	*HRISK*	−1.53 (0.30)
QUITA	*DANGER*	1.21 (0.48)
QUITA	*RISK*	6.95 (2.86)
QUITA	*HRISK*	1.55 (0.42)

[a]Other variables entered in each equation include: *AGE*, *BLACK*, *MALE*, *EDUC*, *MARRIED*, *KIDS*, *EXPER* (in *WPREM* equations), *TENURE* (in all except *WPREM* equations), and *EARNG* (in all except *WPREM* equations).

[b]Asymptotic standard errors are shown in parentheses.

labor market mismatches even with rational behavior if workers have some imperfect knowledge of the risks of the job which they continually update as they acquire additional information through their on-the-job experience.[7] Wage premiums for risk will be observed, but workers in high-risk situations will also tend to quit once they have learned about the risks and have decided that the risk compensation is insufficient. Although past empirical work has focused on worker quitting,[8] a related prediction is that if workers were asked to repeat their job choice based on current information, many workers in high-risk jobs would be reluctant to do so. Unlike worker quitting, this job acceptance question is not influenced by transactions costs of job changes, such as seniority rights. This question also avoids the limitations of the relative risk premium question, which may not fully capture the overall desirability of the job.

For the full sample, 79 percent of the sample would decide without hesitation to take the same job (*TAKEA*). The remaining 21 percent would either have some second thoughts or would definitely not take the job. Since 97 percent of all respondents would, at most, "have some second thoughts" (*TAKEB*), only 3 percent of the sample appears to have strong reservations about their positions. The combination of the wage premium estimates and the widespread willingness to repeat the employment decision suggests that job risks are not a major source of worker dissatisfaction. Few workers appear to be seriously mismatched.

One mechanism by which mismatches are remedied is through worker quitting. To analyze the job hazard-quit relationship, we developed quit intention variables utilizing the same phrasing as did the *Survey of Working Conditions* questions analyzed in Viscusi (1979). As shown in that study, this quit intention measure yielded results that were quite similar to those generated by actual quit behavior. One-eighth of the sample was very likely or somewhat likely to "make a genuine effort to find a new job with another employer within the next year" (*QUITA*), but only 5 percent were very likely to do so (*QUITB*). Some worker dissatisfaction is clearly present, but there is not a large proportion of severely dissatisfied workers at the firms in our sample.

The worker's job risk plays an instrumental role in the cases in which mismatches are observed. Table 3 presents the maximum likelihood estimates for the determinants of two job satisfaction measures. In each case, the equations also included a series of variables, such as worker age, that are strongly linked to worker turnover. The probability that the worker would repeat this job decision (*TAKEA*) is negatively related to all perceived risk variables, controlling for

[7]See Viscusi (1979) for a formal presentation of this model.

[8]The job hazard-quit results in Viscusi (1979) are presented for aggregative quit rates, three national samples of panel quit data (Panel Study of Income Dynamics and two National Longitudinal Surveys), and quit intention data from the *Survey of Working Conditions*.

worker earnings and other related factors. A worker who views his job as dangerous (*DANGER*), for example, will have a probability of repeating his initial job choice that is .22 lower than those who do not. Similarly, all of the job risk variables exert a positive influence on *QUITA*, where the quit intention probability will increase from .06 to .19 —or over triple—if the worker views his job as dangerous. Put somewhat differently, the mean effect of the *DANGER* variable accounts for one-half of all quit intentions.

These results are consistent with a model in which the worker's job choice among potentially hazardous jobs is part of an ongoing adaptive process. Workers' reservation wages will increase as their perceived risks rise so that we will observe risk premiums for prior perceived risks and for some risks discovered on the job. Risk that workers learn about but for which they are not compensated sufficiently will generate quits. While the evidence is consistent with this general view, the intermediate learning linkage and the behavioral implications of changes in risk assessments have not yet been examined.

II. Hazard Information and Risk Perceptions

To obtain evidence on this learning process, we carried out the following risk information processing experiment in the second part of the questionnaire. We presented each worker with a hazard warning label for one chemical that was not a current part of his job. Each respondent was told that he would use 100 lb. containers of this substance within the context of his current job operations, but that this chemical would replace the chemicals with which the individual was currently working. The scenario was similar to that in which a worker learns that the chemicals he uses have been mislabelled. We provided workers with "new information" rather than informing them of existing hazards so as to be able to distinguish the role of the hazard warning from a priori knowledge about the job, thus providing a context in which learning could be observed. We then asked each worker how this change would affect his risk perception and other aspects of his behavior. Subsequent changes in risk perceptions consequently do not reflect an inadequacy in workers' prior judgments, but rather how information regarding a newly introduced risk will alter the assessment of the job's implications.

We assigned workers to one of four different labeling groups: sodium bicarbonate (*CARB*), a lachrymator chloroacetophenone (*LAC*), asbestos (*ASB*), and *TNT*. The *CARB* control group was set at a relatively smaller size since the primary focus was on the implications of the three risky substances. Each of these workers was given the information following a standard chemical labeling format. Representative portions of each label are given below:

> SODIUM BICARBONATE. SPILL: Sweep-up, place in an appropriate chemical waste container...
>
> CHLOROACETOPHENONE. WARNING! LACHRYMATOR—VAPOR AND DUST EXTREMELY IRRITATING. Do not breathe dust or vapor. Wear a self-contained breathing apparatus...
>
> ASBESTOS. DANGER! CANCER HAZARD. Use with a NIOSH-Mesa approved respirator. Use with approved goggles...
>
> TNT—(blend of dry Trinitrotoluene). DANGER! HIGH EXPLOSIVES. MUST BE STORED IN ACCORDANCE WITH FEDERAL REGULATIONS. KEEP IN COOL, DRY, WELL VENTILATED, LOCK-UP AREA...

Workers did not proceed with the rest of the questionnaire until they had been able to answer successfully some basic overall questions to test whether they had read the label. The workers appeared to have little difficulty in this regard since they had substantial experience using chemicals labeled in this manner. Although the information provided was not with respect to a specific risk level but for a chemical hazard for which risk assessments will vary, the responses were

TABLE 4—VARIABLE MEANS FOR EACH LABELING GROUP

Risk Variable	Means of Variables with Alternative Labels			
	CARB	*LAC*	*ASB*	*TNT*
RISK	.12	.10	.09	.10
RISK1	.06	.18	.26	.31
HRISK	.42	.38	.29	.40
HRISK1	.07	.83	.95	.98
WBOOST	.03	.48	.71	.82
Risk Premium[a]	0	$1,919.01	$2,995.59	$5,158.31
NOWAGE	0	.02	.11	.17
QUITA	.23	.10	.13	.10
QUITA1	.00	.23	.65	.73
TAKEA	.67	.82	.80	.76
TAKEA1	.90	.58	.11	.07
Sample Size	31	106	102	96

[a]Risk premium is $Y1 - Y$. The figures are conditional upon facing an increased risk and being willing to accept a finite risk premium.

consistent with the general patterns one might expect. Table 4 summarizes the variable means for each labeling group.

Before analyzing the principal economic implications of the learning process, we will first review the general pattern of the responses and their plausibility. Sodium bicarbonate is a very safe substance, and this label leads to a reduction in the *RISK* variable from .12 to .6 for *RISK1*, where the postscript *1* indicates the post-information analogue of the variable. Besides halving the assessed *RISK* level, *CARB* also dramatically reduced the fraction of workers who believe they face above-average risk. Only one respondent raised his *RISK* assessment (from .05 to .06), but since this worker was in a very low-risk job and had a posterior *RISK1* value identical to the *CARB* subsample mean, this behavior cannot be regarded as irrational.

If *CARB* were the only risk posed by the worker's job, one would expect that the workers would assess this risk as being zero. Even when working with a safe substance, there is, however, a residual risk such as the risk of a safety-related job injury from accidents. Since the *RISK1* value of .06 for *CARB* equals the 1980 and 1981 average BLS injury rate for the chemical industry, the results are not out of line with what one might expect once the chemical hazards have been eliminated. In addition, not all workers may have known what sodium bicarbonate is. The label suggests that it is a very safe chemical, but it does not explicitly state that it is risk free.

The lachrymator was the second safest substance in the labeling group. Workers viewed this chemical as more hazardous than their present environment, as the *RISK* level almost doubled, and the fraction of workers who considered themselves in above-average risk jobs increased by .45. Eleven workers did not revise their risk assessments upward after seeing the *LAC* label, but these workers were in very high-risk jobs; their *RISK* level decreased from .19 to .15, which is still above the average pre-information *RISK* value for the sample. Notwithstanding the absence of any assessed increase in risk for this subgroup, one person indicated that he was somewhat likely to look for a new job (*QUITA1*) even though he had not expressed this intention earlier, producing a minor consistency problem.

The asbestos warning led to a more dramatic response. The riskiness of this substance relative to *TNT* is not clearcut because of the deferred nature of asbestos-related cancers. Asbestos is, however, a very potent carcinogen, and it led workers to triple their assessed *RISK* levels, with almost all workers viewing their jobs as above average in riskiness. Somewhat surprisingly, 5 percent of all workers did not view *ASB* jobs as posing above-average risk. Moreover, a substantial group of 26 workers, most of whom were in very high-risk jobs, did not raise their risk perceptions. The unresponsive group's reservation wage and quit responses (for example, no increase in quits and elimination of all $QUITA = 1$ values) were consistent with their *RISK1* values, so that the *RISK1* variable appears to reflect a more favorable assessment of the job's attractiveness. Such a favorable response is not implausible, particularly for researchers who work with new unregulated carcinogens on a daily basis.

The explosive hazards of *TNT* generated the greatest risk assessment response, as all but two workers now viewed their jobs as above average in risk. Although 11 workers did not raise their *RISK* assessments in response to the warning, these workers were on very hazardous jobs (*RISK* equal to .19), and on average the *TNT* warning lowered their *RISK* value by only .04. There was, however, one seemingly inconsistent respondent who indicated that he was somewhat likely to quit (*QUITA1*) even though he hadn't been earlier, and his assessed *RISK* level had not increased.

As with the earlier results, there is a widespread response to information in the expected direction. The behavior of only a small minority of the workers does not appear consistent with a rational learning process. This result does not, however, imply that workers respond perfectly to new information since the relation between the four labels and actual risk levels is not narrowly defined. Some imprecision is inherent because of differences in individual susceptibility to risk.

To test the empirical implications of the hazard warnings more fully, we will formalize the nature of the learning process. The assumption here is that workers adopt a Bayesian learning approach where their assessed probabilities belong to the *beta* family. This distribution is ideally suited to analyzing independent Bernoulli trials on events such as whether or not one suffers a job accident.[9] We will view the receipt of the new labeling information as equivalent to observing additional Bernoulli trials concerning the riskiness of the job. The implicit assumption is consequently that labels simply serve to augment the risk information available to workers.[10]

The two parameters of the prior distribution are p, the assessed prior probability of an adverse outcome (i.e., *RISK*), and γ, a term that can be regarded as the precision of the prior. After observing m unsuccessful outcomes (for example, accidents) and n successful outcomes, the posterior accident probability $(\gamma p + m)/(\gamma + m + n)$. The term γ is tantamount to the number of trials the worker acts as if he has experienced when forming his prior.

The informational content of each label i likewise depends on two parameters: ξ_i, the precision of the information (i.e., the equivalent number of observations $m + n$ reflected in the information) and s_i, the fraction of these observations that are unfavorable. Whether or not the label raises workers' probability assessments depends on whether s_i exceeds p, and the extent of revision is positively related to the informational content ξ_i, for any given value of s_i. If workers are provided with perfect information and if the labeled chemical is the only risk, the value of ξ_i should be infinite. The labels do not specify the exact chemical risk, so that ξ_i need not be infinite in practice. Moreover, the label only conveys information regarding the risks from direct chemical use so that all accident-related risks and all environmental chemical risks remain. Worker responses consequently will reflect the relative weights workers placed on the prior and posterior information, where these weights will capture both the degree to which the information in the label was credible and the relative role of this risk in the new version of the worker's job.

[9] See John Pratt, Howard Raiffa, and Robert Schlaifer (1975) for more detailed advocacy of the use of *beta* distributions for Bernoulli processes.

[10] If workers do not in fact treat the label as equivalent to additional job experiences but rather "forget" their earlier knowledge, no difficulties are caused provided that the degree of forgetting is determined by the precision of their judgments, not the level of the risk. If the initial risk level were also to affect the weight placed on the label, the empirical estimates would be biased.

The posterior probability p_i of an adverse job outcome after receiving a hazard warning for chemical i is given by

$$(1)\quad p_i^* = \frac{\gamma p + \xi_i s_i}{\gamma + \xi_i} = \frac{\xi_i s_i}{\gamma + \xi_i} + \frac{\gamma p}{\gamma + \xi_i}.$$

The regression equation counterpart of equation (1) for each chemical i is

$$RISK1_i = \alpha_i + \beta_i RISK_i + u_i,$$

where u_i is a random error term and

$$(2)\quad \alpha_i = \frac{\xi_i s_i}{\gamma + \xi_i}; \quad \beta_i = \frac{\gamma}{\gamma + \xi_i}.$$

To take into account the bounded nature of the dependent variable, we will also estimate the equations in terms of the log-odds of the probability, or $\ln(RISK/(1 - RISK))$. In this case, the parameters α_i and β_i for the linear regression counterpart can be derived from the regression results but are not produced as directly.

The estimated versions of the parameters in equation (2) also can be used to construct two key measures of the information conveyed by the warning. The risk level s_i is given by

$$(3)\quad s_i = -\alpha_i/(\beta_i - 1),$$

which can be verified using equation (2). Similarly, the informational content of the warning relative to the prior, Ψ_i, is given by

$$(4)\quad \Psi_i \equiv \xi_i/\gamma = (1/\beta_i) - 1.$$

Higher values of Ψ_i imply greater informativeness of the label compared to the worker's initial judgments.

To the extent that workers' risk responses reflect not only changes in the probability of an adverse outcome but also changes in their severity, one must modify the formulas above. Let V_i be the severity (i.e., monetary equivalent) of the health impact posed by the hazard warning relative to that posed by the average U.S. job injury, which serves as the metric for the analysis. If the *RISK1* responses reflect changes both in the probability of an accident and its severity, equation (3) becomes

$$(5)\quad s_i V_i = -\alpha_i/(\beta_i - 1),$$

and the formulation and interpretation of equation (4) remains unaltered.[11] Although the discussion below will be in probabilistic terms and will not include V_i explicitly, it should be noted that these risks are severity weighted.

Table 5 summarizes the regression results and the parameters calculated from them. Overall, the linear variant of the equation provided a better fit than the log-odds formulation. The coefficients α_i and β_i reflect the nature of the learning process. In the case in which workers' judgments are not affected by the hazard warning and are solely dependent on their prior value of *RISK*, α_i will equal 0 and β_i will equal 1. At the other extreme in which the hazard information is dominant, β_i will equal 0 and α_i will be positive. The regression results were between these two extremes. In all cases the label provided a substantial input, and in two cases the prior continued to play a significant role. These results are broadly consistent with a Bayesian learning model.

In the case of *CARB*, the label lowered the *RISK* assessment but did not eliminate the role of the prior, as both α_i and β_i were statistically significant in the linear case where the relation to equation (2) is direct. The risk level s_1 implied by *CARB* is .04, or under half of the worker's prior *RISK* level, and Ψ_1 implies that the relative precision of

[11]More specifically, let V_0 be the original accident severity and V_i be the severity of the postwarning accident. Suppose that the components of *RISK1* represent a weighted average of these risks and that they take the form

$$RISK1 = (\gamma p/(\gamma + \xi_i))V_0 + (\xi_i s_i/(\gamma + \xi_i))V_i.$$

If we set V_0 equal to 1 (no loss of generality), the values of α_i and β_i are given by

$$\alpha_i = \xi_i s_i V_i/(\gamma + \xi_i) \quad \text{and} \quad \beta_i = \gamma/(\gamma + \xi_i).$$

The severity-weighted results in the text follow directly.

TABLE 5—RISK PERCEPTION AFTER INFORMATION REGRESSION RESULTS

	CARB		*LAC*		*ASB*		*TNT*	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constant	0.030	−3.58	0.14	−2.05	0.25	−1.23	0.31	−0.86
	(0.014)	(0.46)	(0.01)	(0.13)	(0.02)	(0.11)	(0.02)	(0.09)
RISK	0.21	3.23	0.44	3.76	0.14	1.36	0.03	0.11
	(0.10)	(3.56)	(0.10)	(1.12)	(0.14)	(1.03)	(0.13)	(0.76)
R^2	.12	.03	.14	.10	.08	.02	.01	.01
s_i	.038	.042	.239	.274	.289	.325	.317	.315
Ψ_i	3.72	4.98	1.29	0.83	6.43	2.80	31.36	40.67

Note: All cols. (1) are *RISK1* (linear); all cols. (2) are *RISK1* (log-odds).

the hazard warning was 4–5 times that of the prior.

Since the very safe properties of sodium bicarbonate are reasonably well known, one might have expected that *CARB* would result in a larger relative precision estimate and a lower s_1 than was observed. A possible explanation is that workers did not place an infinite weight on a chemical exposure with near zero risk because of the residual risks of the job. These workers will continue to be exposed to a variety of airborne carcinogens and safety-related risks that will be reflected in the posterior *RISK1* values. As the risks captured by the label approach zero, the nonzero risk components of the worker's job become more instrumental since they dominate the role of the label.

The *CARB* label was, however, much more powerful than the *LAC* warning. This label led to the greatest retention of workers' prior beliefs, as the *RISK* coefficients are the largest of any of the regressions. A small impact was not a consequence of any close similarity in the hazard probabilities of *LAC* and *RISK*, since s_2 is over double the prior value of *RISK*. The limited nature of the effect derives from the lower relative precision Ψ_2 of this warning, which had roughly the same informational content as did workers' prior beliefs.

Warnings for the severe risks of *ASB* and *TNT* are so powerful that the prior *RISK* variable plays an insignificant role; only the constant terms enter. The risk levels s_3 and s_4 are somewhat higher than for *LAC*, but the major difference is the precision of the information. Asbestos warnings have roughly the same relative precision as *LAC*, but *TNT* has especially large informational content, roughly 30–40 times that of the prior. Since *TNT* poses well known explosive risks, this result is not unexpected.

Overall, the risk levels s_i implied by *LAC*, *ASB*, and *TNT* were not too dissimilar. The greatest difference was the relative precision associated with these warnings. The impact of a hazard warning does not hinge solely on the implied risk level. In this instance, the informational content of the label proved to be more instrumental in altering workers' probabilistic judgments. To be effective, hazard warnings must convey information in a convincing manner. Otherwise, the weight individuals place on their prior beliefs will dominate in the formation of workers' risk judgments.

III. The Effect of Learning on Worker Behavior

The change in the risk perceptions resulting from the hazard warnings in turn will affect worker behavior if workers make sequential decisions in an optimal manner. The data in the bottom portion of Table 4 summarize the wage and turnover effects, which reflect similar patterns of influence. After reviewing the general nature of these responses, we will use these responses to test the key hypotheses regarding rational worker behavior.

The demand for risk premiums is positively related to the change in the risk, as one would expect. The fraction of workers who indicate that they would require a higher salary to be willing to work with the new chemical (*WBOOST*) is about three-fourths for *ASB* and *TNT*. As noted above, there are some workers with very high initial risk assessments that were not increased as a result of the label so that not all workers will desire extra compensation. The amount of extra compensation demanded ranges from $2,000 for *LAC* to over $5,000 for *TNT*. Workers need no risk premium to work with *CARB*. (Indeed, they should be willing to take a pay cut, but the survey did not address this possibility.) The premium estimates are only for those workers willing to remain on the job in return for extra pay. Some workers, particularly for *TNT* and *ASB*, were not willing to state an acceptable reservation wage (*NOWAGE*). Whether these 29 nonrespondents were unwilling to accept any finite risk premium or simply believed that no adequate risk premium was feasible is unclear.

The effect on worker turnover was particularly dramatic since the experiment altered the risk but did not alter the wage rate. These risks consequently will produce a more dramatic worker response than in a market context where there would be some adjustment in the wage level. The *QUITA1* and *TAKEA1* questions pertained to the attractiveness of the current job, varying only the risk. In the case of *CARB*, there was a 23 percent drop in quit intentions to zero, and an equal increase in the percentage of workers who would repeat their job choice. The lachrymator produced a 13 percent increase in quit intentions and a 24 percent drop in workers willing to repeat their job choice. The strongest effects were for *ASB* and *TNT*, which would lead the majority of workers to quit and almost all workers to be unwilling to repeat their job choice.

An instructive check on the validity of these responses is to analyze whether the behavioral relationship governing the risk premium and quit decisions parallel those in the pre-information situation. Such an analysis will also make possible an explicit test of the impact of the risk s_i implied by the label and its relative precision Ψ_i. Higher implied risks s_i clearly should make the job less attractive. The relative precision of one's risk assessment will also increase workers' reservation wage since, as shown in Viscusi (1979), the value of a risky job is negatively related to the precision of one's risk judgments. Jobs associated with looser probabilistic judgments are more attractive since they offer greater potential gains from experimentation. Workers can terminate uncertain jobs if their learning is unfavorable and reap the high expected rewards from jobs associated with favorable on-the-job experiences. This asymmetry generates a predilection for loose priors. This aspect of adaptive behavior is the most distinctive prediction of the model, but it has never been the subject of an explicit empirical test.

To analyze the effect of the hazard warnings on the level of compensating differentials, we first need some additional notation. Let Y represent initial worker income, X be a vector of all nonrisk variables for that job, Z be the unmeasured effects specific to the job-worker match, and u be the error term. The compensating differential results in Section I focused on an equation of the form

$$(6) \quad Y = \beta X + \beta^* RISK + \beta^{**}\gamma + Z + u.$$

Since γ and Z were omitted from the model, the estimated coefficients were subject to omitted variables bias.

The situation following information (denoted by postscript *1*) can be modelled similarly, where

$$(7) \quad Y1 = \beta X + \beta^* RISK1 + \beta^{**}(\gamma + \xi) + Z + u1.$$

Subtracting equation 6 from equation 7 yields

$$(8) \quad Y1 - Y = \beta^* \Delta RISK + \beta^{**}\xi + u1 - u,$$

where $\Delta RISK$ is $RISK1 - RISK$. Equation (8) will yield consistent estimates of the coefficients in this fixed effects model as the sample size $N \to \infty$ if there is sufficient variation in $\Delta RISK$ and ξ.[12] It should be noted that we do not have information on ξ_i but

[12] Use of the fixed effects model in compensating differentials studies is not unprecedented. See Brown and, more generally, see Gary Chamberlain (1982).

TABLE 6—POST-INFORMATION EARNINGS AND QUIT EQUATIONS[a]

Dependent Variable	*RISK* or Δ*RISK*	*s*	Ψ	$R^2/-2$ Log Likelihood
EARNG	9934.5	6784.2[b]	52.0[b]	.24
	(5468.6)	(3342.3)	(32.2)	
Δ*EARNG*	12435.3	–	65.56[b]	.17
	(2681.9)		(20.10)	
EARNG	9838.3	6602.3[c]	41.6[c]	.24
	(5471.3)	(2684.2)	(19.6)	
Δ*EARNG*	12777.5	–	46.53[c]	.17
	(2640.3)		(14.17)	
LNEARNG	.627	.456[b]	.0021[b]	.28
	(.303)	(.185)	(.0018)	
Δ*LNEARNG*	.633	–	.0027[b]	.31
	(.087)		(.0007)	
LNEARNG	.622	.424[c]	.0018[c]	.28
	(.303)	(.149)	(.0011)	
Δ*LNEARNG*	.651	–	.0019[c]	.31
	(.086)		(.0005)	
QUITA	−1.05	5.95[b]	.027[b]	381.3
	(2.03)	(1.43)	(.013)	
Δ*QUITA*	20.4	–	.011[b]	63.3
	(4.3)		(.029)	
QUITA	−1.07	5.75[c]	.021[c]	384.6
	(2.02)	(1.17)	(.008)	
Δ*QUITA*	20.6	–	.002[c]	63.5
	(4.3)		(.020)	

[a]All cross-sectional equations include other explanatory variables as in Tables 2 and 3.
[b]The Ψ variable is based on the linear regression estimates reported in Table 5.
[c]The Ψ variable is based on the log-odds regression estimates reported in Table 5.

on Ψ_i for each labeling group, which is ξ_i/γ. Workers, however, will differ in the precision of their priors, so that γ will be a random variable. Since the workers were assigned randomly to each labeling group, the precision variable should be subject to random measurement error, biasing the β^{**} coefficient downward.

Table 6 reports the earnings equations both in the first difference form (i.e., Δ*EARNG*, Δ*LNEARNG*) and in the cross-sectional form for the post-information case, where the *RISK* variable is of the same form as the dependent variable (Δ*RISK*). Since the first differencing eliminates the biases from omitted fixed effects, the change in earnings equations will be estimated for the full sample, while the cross-sectional results will focus on the *BC/TECH* subsample as before. In the case of the post-information cross section, we included both *RISK* and *s* rather than *RISK1* in order to estimate explicitly the role of the risk implied by the warning. The results reflect a consistent pattern of premiums for prior risks and risks communicated through the label. Similarly, labels associated with high relative precision Ψ generate additional premiums, as predicted.

The consistency of worker behavior with the earlier results is more difficult to ascertain since premiums per unit of risk should be larger since individuals will demand higher rates of compensation if placed in a highly risky job that is not consistent with their preferences. Whereas the initially perceived risks are the result of a voluntary self-selection process, the post-information risks are not, and serious mismatches may occur. Higher desired premiums per unit of risk consequently should be observed.

The magnitude of the post-information wage-risk tradeoff bears out this pattern. In the case of the linear specifications, for example, the *RISK* and *s* coefficients average about one-fifth higher than in Table 2, while in the first difference form $\Delta RISK$ commands premiums three-fourths larger. A greater response is observed in the first differencing case because the additional desired premiums per unit of risk for the added hazard will be averaged only across the extra risks, whereas the post-information cross section obtains an average unit risk premium for the entire risk level. In addition, about one-third of the discrepency arises because the first differencing results focus on the full sample, which is wealthier than the *BC/TECH* subsample used in the cross sectional results. These workers consequently demand a larger premium per unit risk.[13]

To analyze the change in workers' quit decisions, we can formulate a post-information cross section and an analogue of the fixed effects model for discrete variables.[14] The post-information quit intentions in the cross-sectional results are driven exclusively by the implied risk and precision of the hazard, each of which has the expected positive effect. The most dramatic difference with the earlier results is in the $\Delta RISK$ coefficients in the first difference equations, which are almost three times larger than in the preinformation results in Table 3. Such a dramatic increase is not implausible since quits arising in the market are in response to a pay-risk package mix that the worker initially accepted. Here workers are responding to often dramatic changes in their job's attractiveness so that the intensity of the response should increase. The $\Delta QUITA$ equations do not, however, lead to significant coefficients for Ψ, a result that may be due to the drop in sample size down to 161 as a consequence of the statistical estimation procedure that has been used.

IV. Conclusion

The focus of this analysis has been on an adaptive framework in which individuals do not have perfect job risk information, but instead continually revise their risk judgments in Bayesian fashion and then switch jobs once these judgments become too unfavorable. This theory is an extension of the standard compensating differential analysis rather than an incompatible theory. Workers' initial perceptions of risk led to compensating differentials and also generated intentions to quit and regret over having accepted the job initially. The evidence of risk-related job mismatches is consistent with a model of job experimentation and would not occur in a perfect information version of the compensating differential model. The extent of these mismatches does not, however, appear to be great, so that for this sample the market appears to operate reasonably effectively.

After being given a hazard warning for use of a new chemical in their job, workers revised their risk assessments in the expected directions, but retained some influence of their prior for hazard warnings with low informational content. Although the risk level implied by the label was of consequence, differences in informational content appeared to be more influential in governing one's posterior risk assessment. This learning in turn generated a demand for risk premiums and incentives to quit, as predicted. Both the change in the level of the risk and changes in the precision of workers' judgments were of consequence, as the adaptive model predicts. Although the change in the risk level had a more consistent direct effect on behavior than did the relative precision of the hazard warning, the precision also has an indirect influence through its powerful impact on the posterior risk assessment.

The pivotal influence of the informational content of the chemical label has broad ramifications for the design of effective risk information strategies. Past informational campaigns such as those intended to encour-

[13] Estimation of the *EARNG* and *LNEARNG* equations for the *BC/TECH* subsample yielded annual risk premiums about $1,000 less than for the full sample.

[14] Using the procedure developed by Chamberlain (1980), we will restrict the sample to those individuals who altered their quit decisions since sample observations involving the same quit responses provide no useful information for the estimation. Those (0,1) responses who would quit after the warning but not before (primarily from *LAC*, *TNT*, and *ASB* groups) constitute one of the binary outcomes and the (1,0) responses (primarily from *CARB*) constitute the other outcome. The explanatory variables are the first differences of the variables included in the pre-information equation so that only the risk-related variables remain.

age seatbelt use and deter cigarette smoking have generated disappointing results. The primary purpose of these efforts is that of exhortation rather than providing consumers with information that they did not already possess. The lack of a major consumer response should not be unexpected since the informational content of these warnings was low. The results in this study indicate that risk information programs will be most effective when they do not simply convey the risk level, but they also provide individuals with new information in a convincing manner.

Most workers behaved as expected, but there was a small minority of alarmist responses as well as some inertia and inconsistencies. Moreover, while the empirical evidence constitutes the most refined test of the Bayesian learning model of adaptive job choice, observed consistency with the principal predictions of the theory does not necessarily imply full rationality. Nevertheless, there is strong evidence of a systematic worker response that is quite different from the polar extremes of optimal decisions with perfect prior information and random decisions by irrational workers.

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