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Smoking Status and Public Responses to Ambiguous Scientific Risk Evidence

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Smoking Status and Public Responses to Ambiguous Scientific Risk Evidence

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Situations in which individuals receive information seldom involve scientific consensus over the level of the risk. When scientific experts disagree, people may process the information in an unpredictable manner. The original data presented here for environmental risk judgments indicate a tendency to place disproportionate weight on the high risk assessment, irrespective of its source, particularly when the experts disagree. Cigarette smokers differ in their risk information processing from nonsmokers in that they place less weight on the high risk judgment when there is a divergence in expert opinion. Consequently, they are more likely to simply average competing risk assessments.

1. Introduction

Most risks that we face are not known with precision. The risks posed by climate change, the cancer risks created by breast implants, the potential for adverse reactions to a new drug, and the threat of mad cow disease are all highly uncertain. For example, one prominent British scientist offered the rather imprecise risk judgment that the human form of mad cow disease, or Creutzfeldt–Jakob disease, would kill from 500 to 500,000 British consumers.[1] Such uncertainty is the norm rather than the exception. Substantial ambiguity exists regarding the extent of the hazard even for risks for which there is substantial agreement, such as the hazards of cigarettes. The extent of the health risks posed by environmental tobacco smoke remain hotly debated, as some studies indicate substantial risks and others fail to indicate any significant risk.

How do people respond to situations in which there is a diversity of opinion regarding the level of the risk? Ideally, they should make risk inferences in a rational manner; where we will take Bayesian learning as the rationality reference point. When there are competing scientific risk judgments, how people process the information will depend on their prior beliefs, the precision of their prior beliefs, the risks indicated by the scientific studies, and the weight they place on these studies. There are many ways in which people might use such scientific studies, such as by averaging their implications or placing a higher weight on the more credible study. Some of these changes in risk beliefs in response to new information will be consistent with rational learning, whereas others may not. In this paper, we present original survey evidence in

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[1] See "Mad Cows and Englishmen," *The Economist* (March 30, 1996), p. 25. Also see Viscusi (1998) for a general discussion of risk ambiguity results in the literature.

which respondents consider a variety of information scenarios, making it possible to assess the consistency of the treatment of different scientific risk studies.

To the extent that behavioral predictions are possible based on evidence in the literature, it would suggest that people may exhibit anomalous behavior when there is ambiguity regarding the magnitude of the risk. Consider, for example, the implications of the classic Ellsberg (1961) paradox. In that experiment, subjects considered two urns, one of which offered a known probability of winning a prize, whereas the other offered an uncertain chance of winning a prize. Respondents were averse to ambiguous chances of winning the prize, compared to a lottery ticket with precisely known probabilities and the same mean probability value. Researchers have identified similar phenomena with respect to small probabilities of a loss, because there is often a tendency toward ambiguity aversion that is not consistent with rational expected utility theory.

The issues addressed in this paper represent a variant on this ambiguous risk structure. Moreover, we have coupled the presence of risk ambiguity with different risk information sources, whereas in earlier studies, such as Viscusi and Magat (1987), there is no difference in the source's identity. Suppose that there are two different parties providing risk information, and their views are different. How do people process the divergent risk judgments? Consider the situation of an industrial polluter, which might be expected to have a vested economic interest in downplaying the risk or even misrepresenting it. To what extent does it matter whether the risk evidence is from industry or government? When is individual differentiation between those risk sources entirely rational, and is there any reason to believe that people fail to process diverse risk information rationally?

The substantive focus of the study will be on how people respond to different assessments of the risk of cancer due to air pollution. Cancer is a chief source of individual risk that is often ambiguous. The use of an air pollution context enables us to consider risk estimates in the policy arena, including both business and government. In each case, respondents will consider two different sources of risk information about the potential cancer risk. These informational sources could be both government or industry sources, or possibly a mixture of industry and government sources. Because the polluting firm will have less of an incentive to reveal accurate risk information about the hazards it generates than might the government, an interesting economic issue is how people will process these divergent risk judgments depending on their source and the risk levels associated with them. Unequal weighting of such scientific evidence may be entirely rational. In the case of our study, however, respondents will consider a variety of different informational combinations. Ideally, people should be consistent in how they weight risk evidence across different risk scenarios.

The key issue we explore here is how risk judgments and relative weighting of diverse scientific evidence varies with personal characteristics. Demographic factors may be consequential. Women, for example, have shown themselves to be more averse to facing health hazards than are men.[2] A personal characteristic of particular saliency is individual smoking status. Do people who have self-selected themselves into this extremely dangerous consumption activity process risk information differently than do nonsmokers with similar demographic profiles? The analysis of the distinctive behavior of cigarette smokers with respect to this informational context is of interest since cigarette smoking involves a risk for which there are

[2] Hersch (1996) documents a variety of salient gender differences in attitudes toward health risks.

continuing battles between the cigarette industry and government officials focused on the hazards of environmental tobacco smoke.

The organization of this paper is as follows. Section 2 outlines the theoretical structure for the study and the empirical formulation of the model that will be tested. Section 3 presents the empirical estimates of the effect of the different risk information sources and the different risk levels on individual risk judgments. Section 4 focuses on the role of smoking status and its effect on the processing of risk information. As indicated in the concluding section 5, individuals do not treat the different kinds of information based solely on the credibility of the source. Rather, they tend to place disproportionate weight on the high risk assessment, particularly when there are conflicting risk judgments. Cigarette smokers are less likely to exhibit such alarmist behavior.

2. Theoretical Structure and Empirical Framework

Theoretical Structure

The basis for the study is a survey of adults in which they considered moving to one of two areas, area 1 or area 2. Each area posed a risk of cancer, but they differed in terms of how the risk was characterized. Area 1 posed an uncertain cancer risk level S for which there were two divergent risk judgments involving industry, government, or a mix of sources. Area 2 has cancer risk level R that is estimated with precision and will thus serve as the reference point for the level of the precisely understood risk that is equivalent to uncertain risks. The survey proceeded iteratively using an interactive computer program until respondents identified the known risk R in area 2 that they believed was equivalent to the ambiguous risk in area 1.

The advantage of considering a move to an undefined new area is that respondents will not bring to bear their prior beliefs regarding their current risk situation. Each area was, in effect, an abstraction for which there was only survey information regarding the area's chemical hazards based on two different studies. The study could consequently be a pure informational experiment in which all that transpired was an effort by respondents to find a known risk value that was equivalent to an area in which there were two studies that differed in terms of the implied risk level.

The nature of the informational context is noteworthy as well. For personal risk-taking activities, such as smoking, some researchers have hypothesized that people may discount risk evidence for a risky activity they have chosen. Air pollution, which is the case study for this analysis, is a hazard outside of the individual's control. This risk is involuntary and inflicted by a polluting industry in which the respondent has no economic interest. Moreover, air pollution is a public hazard that poses similar exposures to all, although the actual risks may differ if, for example, one is asthmatic. The survey design consequently avoids any influence of risk perceptions being influenced by a desire to justify relatively great personal risk taking.

The two information sources were scientists from the polluting chemical industry (denoted by i) and scientists from the government (denoted by g). Respondents received no information about the nature of the scientific studies or their timeliness, so there was no reason otherwise to differentiate between them. The Appendix presents sample survey questions.

If we let U denote utility in the healthy state and V denote utility with cancer, the task is for respondents to find the value of the known risk R in area 2 that gives them the same expected utility in both locations, or

$$(1 - S)\,U + SV = (1 - R)U + RV. \tag{1}$$

From the standpoint of the survey structure, respondents are picking the known risk R that satisfies

$$R = S. \tag{2}$$

Thus, the structure of the utility functions and the character of the rewards structure are not consequential because the U and V terms drop out. For this binary lottery, the task is simply to find the precisely understood probability R that is equivalent to the subjective risk assessment S in terms of the attractiveness of the chance of getting cancer in that area.

The nature of the study makes the value of the equivalent precise risk R observable, because that precise risk value is simply the cancer in area 2, where the risk is known. By construction, the survey determines the value of R that is equal to the respondent's subjective risk assessment S, which is not observable. Thus, for S we know the two pieces of risk information that are provided to respondents, which are the low and high risk estimates. Although we do not know how respondents use the information in altering their subjective risk assessment S, we know that the result of this process is to get S equal to R, thus making possible an empirical analysis of how people form their risk beliefs.

To impose some structure on the learning process, we will adopt what we call a "naïve Bayesian" model, in which respondents treat both risk estimates as independent sources of information. For concreteness, let risk perceptions be characterized by the beta distribution, which can assume a wide variety of skewed and symmetric shapes. Suppose that people have prior beliefs p regarding the cancer risk, with associated precision α_0. Thus, the informational content of the prior belief is equivalent to drawing α_0 balls from a Benoulli urn, for which a fraction p indicate a cancer risk. The low-risk information from source j (either industry i or government g) indicates a cancer risk s_{1j} with associated precision α_{1j}. Similarly, the high risk information indicates a cancer risk s_{2k} with associated precision α_{2k} (either industry i or government g). We will refer to information that has a higher precision parameter as being more "credible." A key assumption of this naïve Bayesian model is that the informational weight does not depend on the risk probability value disclosed. Note that there is no requirement that people treat the industry and government sources as being equally credible.

The posterior risk assessment S is a linear weighted average of the different probabilities, or

$$S = \frac{\alpha_0}{\alpha_0 + \alpha_{1j} + \alpha_{2k}}p + \frac{\alpha_{1j}}{\alpha_0 + \alpha_{1j} + \alpha_{2k}}s_{1j} + \frac{\alpha_{2k}}{\alpha_0 + \alpha_{1j} + \alpha_{2k}}s_{2k}. \tag{3}$$

The weights on p, s_{1j}, and s_{2k} are the respective fractions of the total information reflected by each information source, where these fractions sum to 1.0.

By design, the experimental manipulation gave respondents evidence from two studies and did not indicate any overlap between them. If the studies were overlapping and not independent, the interpretation of the information weights changes somewhat, but one is still led to a linear formulation such as that in Equation 3.[3] For example, assuming a normal distribution rather than a beta distribution, the weights on the two risk studies are the amount of information

[3] See Zeckhauser (1971) and Viscusi (1997) for further analysis of the overlapping case.

unique to the two risk studies divided by the total amount of nonoverlapping information. Similarly, in Equation 3 the weights are the fraction of the total information associated with each information source. Thus, the presence of overlapping information simply alters the interpretation of the coefficients.

A variety of symmetry conditions emerge from this formulation. The key property driving these results is that the informational value of a given source is independent of the other information source (i.e., nonoverlapping information). Let Low(*j*, *k*) denote the information weight on the low risk assessment when the low risk value is from source *j* and the high risk value is from source *k*. The high risk information weight High(*j*, *k*) is defined analogously. If the same party is providing both risk judgments, the information weights should be the same because there is no reason given in the survey for why a high or low risk value from an identical source should differ in terms of credibility. Consequently,

$$\text{Low(i, i)} = \text{High(i, i)}, \tag{4}$$

and

$$\text{Low(g, g)} = \text{High(g, g)}. \tag{5}$$

When there are two information sources, the weights implied by Equation 3 always give the same weight on a particular party's risk information, whether it is the high or low risk judgment, or

$$\text{Low(g, i)} = \text{High(i, g)}, \tag{6}$$

and

$$\text{Low(i, g)} = \text{High(g, i)}. \tag{7}$$

Equally credible information for both parties, which is the situation in which the precision parameter is the same for both parties, leads to Low(*j*, *k*) = High(*j*, *k*) in all instances.

Deriving Equations 4–7 simply involves implementing Equation 3 for the specific case indicated. The precision parameter depends on the information source, not on the implied risk value, so the informational content of a government study is α_g and is α_i for an industry study. Thus, we have

$$\text{Low(i, i)} = \alpha_i/(\alpha_0 + \alpha_i + \alpha_i), \tag{8}$$

which is identical to High(i, i). Similarly,

$$\text{Low(g, i)} = \alpha_g/(\alpha_0 + \alpha_g + \alpha_i), \tag{9}$$

and

$$\text{High(i, g)} = \alpha_g/(\alpha_0 + \alpha_i + \alpha_g), \tag{10}$$

which satisfies Equation 6. The other conditions also follow in a straightforward manner.

One could envision more complicated learning processes that were rational and did not satisfy the properties of this naïve Bayesian model. People's processing of risk evidence may depend not only on the party making the assessment but also on the risk estimate. For example, results from industry studies may have a greater effect when the estimates are high if people believe that the industry would conceal unfavorable information unless it was particularly compelling. The empirical analysis will permit a broad analysis of such influences. However, the interpretation of whether results imply a form of irrationality hinges on adoption of the naïve Bayesian model specified above.

Empirical Formulation

Implementing Equation 3 empirically is straightforward. The dependent variable is the equilibrating known risk R that respondents equated to their subjective risk assessments S for the area with uncertain risk assessments. Thus, for purposes of estimating Equation 3 empirically, the dependent variable equals R. The prior beliefs term in Equation 3 is not observable, but it can be captured by a constant term β_0 and a linear function $\beta_1'X$ of a vector X of personal characteristics. However, the information weight $\alpha_0/(\alpha_0 + \alpha_{1j} + \alpha_{2k})$ depends on the identity of the two information sources, as these affect the values of α_{1j} and α_{2k} in the denominator. To capture this influence, separate dummy variables will be included for the particular information source combination (e.g., industry for the low risk study and government for the high risk study), thus permitting the value of β_0 to vary. The coefficients β_2 of the low risk estimate s_1 and the coefficient β_3 of the high risk estimate s_2 represent the relative informational content of those risk assessments as well. These values will also be permitted to vary to reflect the particular information combination that is present. Abstracting from the complications arising because the coefficients vary with information combination (j, k), the estimating equation is of the form

$$S = \beta_0 + \beta_1 x + \beta_2 s_1 + \beta_3 s_2 + \epsilon, \tag{11}$$

where ϵ is a random error term. The values of β_0, β_2, and β_3 will be invariant with respect to (j, k) in the case of separate regressions performed within different (j, k) information combinations. However, in runs using the pooled data, these β_2 and β_3 parameters will be permitted to vary with each of the information source combinations (j, k). If we let the government–government information case be the baseline situation, or the omitted dummy variable group, the pooled estimating equation is

$$\begin{aligned} S = {} & \beta_0 + \beta_0(\text{i, i}) + \beta_0(\text{g, i}) + \beta_0(\text{i, g}) + \beta_1 X + \beta_2 s_1 + \beta_2(\text{i, i})s_1 + \beta_2(\text{g, i})s_1 \\ & + \beta_2(\text{i, g})s_1 + \beta_3 s_2 + \beta_3(\text{i, i})s_2 + \beta_3(\text{g, i})s_2 + \beta_3(\text{i, g})s_2 + \epsilon. \end{aligned} \tag{12}$$

Even permitting the relative information weights to vary with the information type may not be a sufficiently general formulation. The information content parameters α_0, α_{1j}, and α_{2k} in Equation 3 may vary with personal characteristics. Section 4 will explore the most salient of these interactions, which is the relationship between smoking status and the information weights.

The Data Base

The sample used in this study consisted of 143 adult participants, who were recruited by a market research firm to participate in the study. The Appendix summarizes the sample characteristics. Respondents took the survey using a computer program that proceeded interactively until the equilibrating R value was obtained. The sequence of pairwise comparisons varied depending on the respondent's previous answers so as to produce convergence. The computer format also eliminates interviewer bias and may produce more accurate responses to sensitive questions dealing with personal characteristics, such as age.

Table 1. Mean Indifference Points for Respondents by Information Source

		Information Source Combinations			
Scenario	Overall Mean	(i, i)	(g, g)	(i, g)	(g, i)
(80,100)	94.92	100.26	91.49	99.00	89.90
(10,200)	112.90	107.78	115.59	125.03	107.35
(100,300)	208.71	200.61	210.61	221.25	213.11
(200,400)	310.63	295.92	332.88	318.88	315.74
(615,735)	689.69	695.38	666.89	623.75	722.20
(100,900)	548.53	551.54	605.51	547.06	504.59

As is indicated in the sample questions in the Appendix, the respective risks in area 1 and area 2 were for "the chance of getting cancer from the pollution in each area." The different information combinations received by respondents were two government studies (g, g), two industry studies (i, i), an industry low risk study with a government high risk study (i, g) and a government low risk study with an industry high risk study (g, i).

The different levels of cancer risks varied across subjects and information sources. The survey included six different risk combinations for each information source combination, where the risks were in terms of cases of cancer per million residents in area 1: (100, 300), (200, 400), (100, 900), (10, 200), (80, 100), and (615, 735).

Table 1 provides a summary of the mean responses for each of the six scenarios and each of the four informational combinations. In every case, the overall mean responses were somewhat greater than the midpoint of the range of the two studies. The risk range varied both in absolute and percentage terms because the nature of the responses was not clear *a priori.* For example, in comparing the responses to (100, 300) to (100, 900), one might hypothesize that people would focus more on the high risk estimate when the studies become more disparate. Or they might simply dismiss the high risk estimate if the low risk value was from a more credible source, as in the case of the (g, i) results for (100, 900), for which the response is 505, which is well below the overall sample mean. Because of the substantial differences in responses across individuals, the subsequent regression results are more illuminating in highlighting the patterns of interest.

3. Empirical Results for Basic Learning Models

The regression estimates of equation 12 appear in Table 2. These estimates are for the entire sample, where results from the different types of information provided to the respondents are pooled in a single regression. In each case, the dependent variable is the equilibrating risk (i.e., the number of cancer cases per one million population) in area 2 that the respondent found to be indifferent to the situation in area 1, in which two risk assessments were provided. Subsequent results will disaggregate the findings by information group, but there are no significant differences between the pooled and aggregate results.[4]

Column 1 in Table 2 includes the basic elements of the risk belief model. In recognition of the individual's prior risk beliefs, the equation includes an intercept term as well as a series

[4] The pertinent F-tests suggest that pooling is appropriate.

of personal characteristic variables pertaining to the respondent's age, race, gender, years of schooling, income level, and marital status. Column 1 in Table 2 permits the intercept term to vary across different information combinations. The equation includes dummy variables for the particular information group in which the respondent participated. For example, government–industry pertains to the situation in which the low risk value was from the government, and the high risk assessment was from industry. Thus, the informational content provided by the scientific studies can potentially influence the degree to which prior risk beliefs affect the overall risk perception by altering the relative weight accorded to one's prior beliefs.

Table 2 reports the coefficient estimates and the standard errors in parentheses. Use of ordinary least squares to estimate the regression in a situation in which the dependent variable is bounded (i.e., it cannot be below zero) creates potential problems of heteroskedasticity; as a result we also report the heteroskedasticity-adjusted standard errors in brackets.[5] Moreover, appropriate calculation of the standard errors must also take into account that respondents considered multiple risk information scenarios. To account for such influences, the bracketed standard errors are the robust and clustered standard errors shown in brackets, which were calculated using the procedure described in Huber (1967). The linear model in Equation 12 offers the strength that it is directly linked to the theoretical structure in Equation 3, which is also linear.

From a Bayesian learning standpoint, the principal variables of interest in Table 2 are the coefficients on the low and high risk variables. These weights simply represent the relative proportion of risk information associated with the low and high risk information; that is, the fraction of the available information linked to each source. Based on the theoretical model in Equation 3 above, these proportions will sum to 1.0 if no weight is given to the prior belief and will be less than 1.0 if there is some nonzero proportion of the informational content accorded to the prior. If the two risk assessments are treated symmetrically, then these coefficients will be equal. In the extreme situation in which respondents view the risk studies as being the dominant source of information and the prior risk beliefs have no role whatsoever, the sum of the low and high risk coefficients will equal 1.0. If prior risk beliefs are consequential, then the sum of the low and high risk coefficients will be less than 1.0. The estimated sum of these coefficients is 1.01 (column 1), but this value is not significantly different from 1.0.[6] This result is consistent with the prediction of the Bayesian learning model that the informational weights on the low and high risk information sources should sum to a value less than or equal to 1.0. One can, however, reject the hypothesis that the information weights are equal, because the high risk weight is greater.[7] The naïve Bayesian model's symmetric treatment of information can be rejected. People do not treat the information with equal weight but, instead, accord a greater weight to the higher risk judgment. The information source dummy variables are not statistically significant so prior beliefs are not affected by the source, as is consistent with the theory.

[5] For the analogous linear probability models, estimates of the coefficients will not be efficient so that a heteroskedasticity adjustment is appropriate. See Maddala (1983, pp. 15–16). In our case, the dependent variable is not a 0–1 dichotomous variable, nor is it censored or truncated, as the values of the variable should naturally fall in the interval [0, 1]. There were no predicted values outside the [0, 1] range, so the endpoint constraints were not binding.

[6] To explore whether the value of the sum of the two risk coefficients was different from 1.0, column 1 in Table 2 was reestimated, replacing Low Risk and High Risk by (Low Risk + High Risk)/2. The estimated coefficient is 1.038 with an associated standard error of 0.021, so that 1.0 is within the confidence interval.

[7] One can reject the hypothesis that the Low Risk and High Risk coefficients are equal, as the associated F-statistic is 10.52 and the critical $F_{0.05}(1884)$ is 3.84.

Table 2. Risk Perception Regression Results for Pooled Information Groups[a]

	Coefficients (Standard Errors) [Robust and Clustered Standard Errors]		
	1	2	3
Intercept	30.327	41.294	31.041
	(26.622)	(28.347)	(28.502)
	[40.303]	[39.612]	[40.260]
Low Risk	0.455*	0.577*	0.581*
	(0.022)	(0.039)	(0.041)
	[0.023]	[0.054]	[0.061]
High Risk	0.559*	0.498*	0.520*
	(0.015)	(0.026)	(0.027)
	[0.019]	[0.030]	[0.029]
Industry–Industry	0.895	−7.912	−7.800
	(9.093)	(16.551)	(16.498)
	[6.739]	[12.088]	[12.069]
Government–Industry	11.755	−5.826	−5.488
	(10.576)	(19.208)	(19.146)
	[8.357]	[13.552]	[13.475]
Industry–Government	2.815	15.869	17.761
	(11.898)	(21.734)	(21.674)
	[8.654]	[15.471]	[15.694]
Low Risk × Industry–Industry		−0.113	−0.119
		(0.054)	(0.054)
		[0.078]	[0.077]
High Risk × Industry–Industry		0.064	0.067
		(0.038)	(0.037)
		[0.049]	[0.049]
Low Risk × Government–Industry		−0.244*	−0.246*
		(0.058)	(0.058)
		[0.082]	[0.082]
High Risk × Government–Industry		0.139*	0.139*
		(0.040)	(0.040)
		[0.062]	[0.062]
Low Risk × Industry–Government		−0.236*	−0.241*
		(0.077)	(0.077)
		[0.125]	[0.127]
High Risk × Industry–Government		0.057	0.054
		(0.051)	(0.051)
		[0.065]	[0.066]
Age	−0.556	−0.533	−0.531
	(0.315)	(0.314)	(0.313)
	[0.562]	[0.537]	[0.538]
Age Missing	2.322	0.792	0.676
	(21.596)	(21.572)	(21.502)
	[49.519]	[47.402]	[47.430]
Nonwhite or Other	23.982*	20.307	20.304
	(7.935)	(8.138)	(8.111)
	[14.478]	[14.177]	[14.192]
Male	−15.969	−14.785	−14.664
	(7.900)	(7.859)	(7.833)
	[14.231]	[13.476]	[13.468]

Table 2. Continued

	Coefficients (Standard Errors) [Robust and Clustered Standard Errors]		
	1	2	3
Education	−0.328	−0.522	−0.513
	(1.440)	(1.433)	(1.428)
	[2.337]	[2.391]	[2.393]
Income	4.9E-5	2.2E-5	1.9E-5
	(17.9E-5)	(17.9E-5)	(17.9E-5)
	[22.1E-5]	[21.6E-5]	[21.6E-5]
Income Missing	−5.423	−9.805	−9.882
	(13.531)	(13.448)	(13.404)
	[19.532]	[19.973]	[19.965]
Single	−27.074*	−19.531	−19.506
	(8.361)	(8.392)	(8.364)
	[11.899]	[12.026]	[12.036]
Smoker		−19.687*	14.293
		(8.718)	(15.150)
		[11.737]	[9.219]
Smoker × Low Risk			−0.003
			(0.047)
			[0.047]
Smoker × High Risk			−0.076*
			(0.033)
			[0.040]
$\bar{R}^2$	0.81	0.82	0.82

Asterisks denote coefficients that are statistically significant at the 95% confidence level, one-tailed test, using the heteroskedasticity-adjusted standard errors.
[a] The sample size is 858 for all columns.

Column 2 in Table 2 explores the character of the influences on risk beliefs in much greater detail. In particular, both the low and high risk coefficients interact with three of the four informational sets to reflect the possible different information weights for the parties. The omitted interaction is for the g–g combination. These differences are statistically significant, because one can reject the hypothesis that this set of interactions is zero.[8] This informational combination forms the baseline risk coefficient estimates in column 2, as respondents place a relative weight of 0.58 on the low risk information provided by the government and a weight of 0.50 on the high risk information provided by the government.

To obtain comparable estimates of the effect of different information sources on the informational weights, one must add the coefficient of the interaction term to these low and high risk coefficients. As it turns out, it matters a great deal who has provided the risk information. In the case of the i–i interaction set for which all information is from industry, the low risk weight is less than that for the g–g combination, and the high risk weight is higher than the g-g combination. These differences are statistically significant for the unweighted standard errors but not for the heteroskedasticity-adjusted standard errors. The relative weight on the high risk information is 0.56, compared with a relative weight of 0.46 on the low risk information. The

[8] The pertinent F-statistic for the constraint imposed by column 1 compared with column 2 in Table 2 is 4.22, and the critical $F_{0.05}(7837)$ value is 2.03.

point estimates for the i–i mix of information leads to a higher weight on the high risk outcome than the low risk outcome, which is a reversal of the pattern observed for the g–g information set.

The differences become particularly stark and statistically significant once there is a mix of risk information sources. In the case of the g–i risk information combination, the low risk information provided by the government has a much lower weight than in the g–g combination, and the high risk information provided by the industry has a more substantial weight. If the polluting industry itself believes the risk is likely to be high, people are particularly likely to believe that estimate as opposed to a lower risk estimate by the government. The net result is that in the g–i situation, the informational weight placed on the government risk information is 0.33, and the weight placed on the industry information is 0.64, or almost twice as much. In the situation where there is a discrepancy between the information sources, the industry information at the high risk end receives a very high weight, even higher than in the situation in which the industry was the source of both the low and high risk information. Perhaps somewhat surprisingly, the high risk assessment by industry is more consequential when the low risk assessment is given by the government risk experts, compared with experts from the polluting firm.

The final variant of information that is provided is the i–g risk information case. Do people dismiss the polluting industry's risk estimate when the government studies suggest the risk is higher than do the industry's? The low risk weight for the industry risk information in the i–g situation is smaller than the weight placed on the government low risk information in the g–g case. The net effect is that the relative weight placed on the industry low risk information in the i–g case is 0.34, and the relative weight placed on the government low risk information is 0.57.

Respondents treat the high risk information as being more informative. This pattern is borne out in the interaction results, especially in the g–i and i–g cases in which there are different information sources. This predilection for treating worst case scenarios as more consequential is consistent with observed biases in government risk regulation programs as well, because these risk policies tend to be guided by the maximum risk level or the upper end of the 95% confidence level of the risk range (see Nichols and Zeckhauser 1986; Viscusi 1992a). Individual respondents display a similar orientation in that fear of the worst case scenario receives greater weight than does the low risk assessment.

This pattern reflects what one might view as risk aversion in learning. When faced with a lottery on two risk assessments, the informationally risk-averse respondents have a certainty equivalent probability that is higher than the expected value because of the disproportionate weight on the high risk assessment.[9] Such risk aversion in learning appears more prevalent when different parties are the sources of the conflicting judgments. This phenomenon is, however, independent of the shape of individual preferences and the presence of risk aversion for changes in wealth.

Table 3 reports the regression estimates for Equation 11 for each risk information subsample. These results parallel the earlier findings almost identically. In the g–g risk information case, the low risk information weight is 0.58, and the high risk information weight is 0.50. The i–i informational weights are almost identical to those implied by Table 1: the low risk weight

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[9] With normal risk aversion, 11 individuals facing a lottery will attach to it a certain monetary equivalent below its expected value.

Table 3. Risk Perception Regression Results for Different Information Groups

	Coefficients (Standard Errors) [Robust and Clustered Standard Errors]			
	Government–Government	Industry–Industry	Government–Industry	Industry–Government
Intercept	46.244	72.783	−7.689	8.326
	(43.308)	(48.499)	(65.626)	(71.663)
	[36.774]	[58.378]	[57.600]	[69.008]
Low Risk	0.582*	0.467*	0.329*	0.341*
	(0.036)	(0.039)	(0.048)	(0.068)
	[0.055]	[0.060]	[0.055]	[0.101]
High Risk	0.498*	0.561*	0.640*	0.555*
	(0.024)	(0.029)	(0.034)	(0.045)
	[0.030]	[0.039]	[0.050]	[0.055]
Age	−0.506	−0.720	−0.048	−0.815
	(0.509)	(0.565)	(0.779)	(0.839)
	[0.613]	[0.665]	[0.772]	[0.613]
Age Missing	−29.714	−1.475	41.326	20.248
	(34.826)	(38.823)	(52.844)	(59.116)
	[56.151]	[54.328]	[47.444]	[47.726]
Nonwhite or Other	30.688*	12.966	15.233	22.395
	(13.175)	(14.658)	(19.751)	(22.488)
	[16.168]	[17.773]	[20.742]	[19.738]
Male	−13.188	−16.097	−26.356	−0.277
	(12.697)	(14.257)	(19.366)	(20.812)
	[13.668]	[15.859]	[19.327]	[23.282]
Education	−0.690	−2.742	1.108	2.922
	(2.320)	(2.586)	(3.649)	(3.679)
	[2.018]	[3.421]	[3.761]	[4.257]
Income	4.3E-5	3.7E-5	4.1E-5	2.4E-5
	(29.0E-5)	(32.5E-5)	(43.2E-5)	(50.9E-5)
	[24.0E-5]	[25.4E-5]	[27.7E-5]	[38.2E-5]
Income Missing	−19.778	11.638	−2.909	−43.830
	(21.796)	(24.269)	(33.037)	(36.167)
	[20.297]	[23.533]	[29.243]	[47.805]
Single	−25.637*	−21.570	−15.174	−4.403
	(13.554)	(15.024)	(21.134)	(22.384)
	[14.528]	[14.824]	[18.249]	[22.122]
Smoker	−31.182*	−24.560*	−2.163	−5.576
	(14.105)	(15.728)	(20.879)	(24.512)
	[14.983]	[12.466]	[15.278]	[24.777]
$\bar{R}^2$	0.83	0.81	0.83	0.78
N	286	286	168	118

Asterisks denote coefficients that are statistically significant at the 95% confidence level, one-tailed test, using the heteroskedasticity-adjusted standard errors.

is 0.47, and the high risk weight is 0.56. Similarly, the g–i low risk weight is 0.33, and the high risk weight is 0.64, as in the pooled regression case; in the i–g case the low risk weight is 0.34, and the high risk weight is 0.56. Permitting all the coefficients to change and not simply the risk information variable consequently has negligible effects on the influence of the relative informational weights on the two different information sources presented to respondents.

There are, however, some notable differences. In particular, the race, marital status, and smoking status variables are statistically significant in the g–g case, but only smoking status is ever significant in the other separate informational group regression results. Overall, risk perceptions tend to be higher for nonwhites and for single respondents, and they tend to be lower for smokers.

The nature of the departures from rational behavior is reflected in the character of the divergences of the estimates in Table 3 from the predicted parameter relationships. Equations 4, 5, 6, and 7 above summarize the various symmetry hypotheses for the naïve Bayesian model on which they are based. This reference point assumes that informational weights depend only on the particular source and not on the risk estimate or the other information provided. Consequentially, "irrational" observed behavior may be consistent with other, more complex rational learning models. The first set of symmetry hypotheses in Equations 4 and 5 state that in situations in which both high and low risk information are from the same party, the relative informational weights should be identical. The low risk weight is greater in the g–g case, and the high risk weight is greater in the i–i cases. These differences are statistically significant in both the Low(g, g) and High(g, g) case, as well as for the Low(i, i) and High(i, i).[10] In each instance, however, the magnitudes of the differences are not great, as the weights are roughly 0.5.

Substantial differences arise once information is provided by different information sources. The informational weight conditions characterized by Equations 6 and 7 are each violated.[11] Moreover, there is a consistent pattern to the violations because the high risk weight is consistently larger than the low risk weight irrespective of whether the high risk information is from the government or industry. It is not so much the identity of the party conveying the high risk information but, rather, the fact that there is a diversity of views. As one would expect, the gap between the high and low risk informational weights is greater when the high risk assessment is from industry, but in each case there is a substantial spread between the size of the informational weights, ranging from 0.23 to 0.30. In situations in which there is a diversity of views, respondents place from one and one-half to two times as great a weight on the high risk assessment as on the low risk assessment.

Many of the disparities that are observed reflect consistent patterns of influence. When there are different information sources, the low risk weight is not significantly different for either Low(g, i) = 0.33 or Low(i, g) = 0.34.[12] Similarly, the high risk weights High(g, i) = 0.64 and High(i, g) = 0.56 are fairly similar in magnitude and not statistically distinguishable.[13] Similarly, one cannot reject the joint hypothesis that Low(g, i) = Low(i, g) and High(g, i) = High(i, g).[14] That there is a diversity of opinion seems to be more consequential than the identity of the diverse views. The parallels of the estimated low and high risk weights are substantial but not complete when both information sources are identical. The high risk weights—High(g, g) = 0.50 and High(i, i) = 0.56—are not significantly different, but the low risk weights—

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[10] The pertinent F-statistic for the hypothesis that Low(g, g) = High(g, g) is 20.39, which is above the critical $F_{0.05}(1837)$ value of 3.84, and the F-value for the hypothesis that Low(i, i) = High(i, i) is 4.89, which is just above the cutoff level.

[11] More specifically, the F-statistic for the hypothesis that Low(g, i) = High(i, g) is 13.06, and the statistic for the hypothesis that High(g, i) = Low(i, g) is 16.39, each of which exceeds the critical $F_{0.05}(1837)$ value of 3.84.

[12] The pertinent F-statistic is 0.010, which is below the critical $F_{0.05}(1837)$ value of 3.84.

[13] The calculated F-statistic is 2.34, which is below the cutoff value of 3.84.

[14] The F-statistic here is 1.47, while the critical $F_{0.05}(2837)$ is 4.61.

Low(g, g) = 0.58 and Low(i, i) = 0.47—do differ.[15] From the standpoint of the predictions of a rational learning model, these values need not be identical, but they could be in the naïve Bayesian case in which information from both parties is equally credible.

The effect of these kinds of influences are also reflected in the hypotheses that one would develop if government information were more credible than industry information. The outlier is Low(g, i), because the relative information weight given to the industry's high risk assessment in this context is so large that the fraction of the informational content accorded to the government's low risk value is reduced, leading to a violation of the hypothesized dominance of government risk information. The expected large weight that government risk information should receive in the presence of industry risk information is consequently not borne out because of the substantial attention commanded by the industry's high risk assessment in a situation of conflicting risk viewpoints. Similarly, if government risk information were dominant, one would expect High(g, i) to be the smallest entry among the information combinations, whereas in fact, it is the largest because of the extreme weight that respondents place on the high risk estimate provided by industry when the other party providing risk information is the government.

The situation in which industry information is more credible appears less plausible *a priori* and can also be rejected. The largest expected informational weight when industry risk information is dominant is for Low(i, g), which is close to being the smallest.

Overall, the greatest departures from the predictions of the Bayesian learning model pertain to the context in which individuals receive information from different sources. In these contexts, the weight given to the high risk assessment is excessive given the informational content generally accorded to that information source. In other respects, behavior is quite reasonable. Individuals display a responsiveness to the information provided, with positive information weights that sum to an amount that is not statistically distinguishable from 1.0.

One should be cautious in making judgments concerning the rationality of this behavior. The information weights were not consistent with the naïve Bayesian model, in which information from the same source was accorded a weight that was independent of the particular risk value. However, more complicated kinds of learning may be taking place. For example, the most extreme departure that was apparent is that high risk estimates by the polluting industry play a dominant role in situations in which the government provides the low risk assessment. Given the substantial financial interest that the polluting industry would have in not disclosing the high risk level, particularly when government officials believe that the risk is lower, one might conclude that the risk must in fact be quite large for the industry to make such a disclosure. What is implied by the results is that the characteristics of the learning process do not satisfy a learning model in which respondents treat the credibility of the risk information source as independent of the stated risk values. The informational context of the divergence of expert opinions plays an important role in influencing risk beliefs.

4. Smoking Behavior, Personal Characteristics, and the Processing of Risk Information

As a group, smokers face extremely high risks as part of their smoking activities, with lifetime smoking-related mortality risks on the order of 0.18–0.36 (Viscusi 1992b, p. 70). More-

[15] The pertinent F-values are 2.95 for the high risk weights and 4.40 for the low risk weights, where the critical $F_{0.05}(1837)$ value is 3.84.

over, these mortality risks are the subject of substantial public information efforts, both on the part of the government and the media. How do smokers think about risks in nonsmoking contexts? Examination of the risk perceptions of smokers and their responses to this experiment consequently may provide insight into whether smokers process risk information differently than do nonsmokers, where this process may also be at work in determining their smoking risk judgments. Smokers also may respond differently to risk information because they have smoked in a context in which there have been competing extreme informational claims, particularly with regard to the hazards of environmental tobacco smoke. This familiarity with self-interested information provision may affect how smokers interpret risk information more generally.

The pooled information group results in Table 2 (column 2) indicate that, overall, smokers have lower risk perceptions. However, this specification forces the effect of smoking status into the constant term, which reflects prior beliefs, and does not permit smoking status to affect how the information is processed. Once the smoker–risk information interaction terms are included (Equation 3 of Table 2), smoking status alone is not influential in determining risk perceptions. Smokers do not have systematically lower risk beliefs because of lower prior risk assessments. Rather, their risk perceptions are lower because smokers place a lower weight on the high risk information provided to them. The mean effect of this difference is to decrease their risk perceptions by 33 cases of cancer per million, or 11% of the sample mean. A useful comparison is with actual smoker risk beliefs in the cigarette context. Smokers believe the lung cancer risks due to smoking are 14% lower than do nonsmokers, which is a similar discrepancy in the level of risk beliefs (Viscusi 1992b, p. 69). These lower smoking perceptions of smokers relative to nonsmokers also significantly increase the probability that these individuals smoke (Viscusi 1992b, Chapter 5). Risk-taking activities such as smoking consequently reflect a self-selection phenomenon in which the people who assess the activity as being relatively safe will be more inclined to engage in it. Similar risk information processing in other domains also could account for smokers' greater proclivity to engage in high-risk activities more generally. Smokers, for example, are more likely to be injured at home, work on more hazardous jobs, are more likely to be injured at work (controlling for objective job risks), require less compensation to bear risk, and take fewer preventive actions (e.g., flossing one's teeth or checking one's blood pressure).[16]

To explore the role of smoking behavior in greater detail, Table 4 reports the interactions of these smoking status coefficients with the two risk information variables for each of the risk information subsamples. In the case of the g–g information combination, smokers place a lower weight on the high risk information presented to them, but not on the lower risk. The same is true of the i–i risk information combination. The only exception is that in which the source of the risk information is different. In the i–g case, smokers discount the industry's low risk information altogether and place a lower weight on it. Smokers place the same weight on the high risk information as do nonsmokers, but by discarding low risk information, smokers reduce the point estimates of their risk perceptions in the i–g case by 95 cancer cases per million, or 31% of the sample mean. Taken at face value, this result would be consistent with the view that smokers dismiss industry reassurances when the government claims the risk is higher. This situation closely parallels real risk contexts in which government risk estimates are typically greater. Smokers also have a much lower risk perception overall for the i–i case. Smokers will

[16] See Hersch and Viscusi (1998) for documentation of these differences.

Table 4. Selected Coefficients for Risk Perception Regressions with Smoking Interactions[a]

	Coefficients (Standard Errors) [Robust and Clustered Standard Errors]			
	Government–Government	Industry–Industry	Government–Industry	Industry–Government
Low Risk	0.586*	0.432*	0.332*	0.448*
	(0.044)	(0.047)	(0.058)	(0.073)
	[0.072]	[0.085]	[0.068]	[0.065]
High Risk	0.535*	0.596*	0.650*	0.534*
	(0.028)	(0.035)	(0.041)	(0.048)
	[0.030]	[0.057]	[0.062]	[0.051]
Smoker	27.085	2.898	14.973	31.213
	(24.652)	(27.289)	(37.214)	(41.421)
	[16.555]	[17.449]	[22.618]	[52.607]
Smoker × Low Risk	0.0009	0.108	−0.009	−0.517*
	(0.078)	(0.085)	(0.106)	(0.159)
	[0.102]	[0.091]	[0.112]	[0.380]
Smoker × High Risk	−0.133*	−0.108*	−0.033	0.090
	(0.054)	(0.061)	(0.076)	(0.100)
	[0.073]	[0.061]	[0.105]	[0.161]
$\bar{R}^2$	0.84	0.82	0.83	0.80

Asterisks denote coefficients that are statistically significant at the 95% confidence level, one-tailed test, using the heteroskedasticity-adjusted standard errors.

[a] Variables included in regression but not shown are age, age missing, nonwhite or other race, male, education, income, income missing, and single.

have the same risk perception as nonsmokers in the g–i case, in which the industry believes the risks are higher than does the government, generally an atypical scenario.

When there is a consensus in risk beliefs, smokers will discount the high risk assessment, and when industry assesses the risk as being lower than the government, smokers also have a very low posterior risk assessment. Somewhat strikingly, when the smoker variable does not interact with the risk information variables, it is never statistically significant (Table 4). Smokers do not differ significantly in their prior risk beliefs. The principal manner in which smokers differ from nonsmokers is not differences in prior beliefs, but rather differences in how they process the risk information they receive.[17]

5. Conclusion

Decisions involving risk are complicated and are associated with a wide variety of documented anomalies in individual behavior. It is not surprising that when these decisions become

[17] Although smoking status is the key personal characteristic of policy interest, both marital status and race also were occasionally statistically significant variables as well. To distinguish whether these influences represent a difference in prior beliefs or the processing of information, the same statistical explorations undertaken above for smoking status were also undertaken for whether the respondent was single or nonwhite. In each case, the demographic dummy variables were insignificant. The only significant effect of single marital status is that single respondents place a smaller weight on the low risk assessment in the i–i information case. Nonwhite respondents place a greater weight on the low risk information in the i–g case. Differences in processing information seem to account for more risk perception differences than do differences in prior beliefs.

muddled further by the presence of conflicting risk judgments that people may not respond in a fully rational manner to the risk ambiguities that are present. This study explored individual risk judgments in the presence of conflicting risk information regarding the cancer risks from hazardous chemicals. The possibility that there might be differing views from industry and government scientists as well as different combinations thereof are reflected in a realistic portrayal of the kinds of disparate information that people may receive in actual risk contexts.

One way people might process conflicting risk information is to simply average expert beliefs, treating them as being equally credible. This symmetric treatment may be rational, but it is not a requirement for rationality. A more general formulation of rational learning is to treat each information source in a consistent manner, which is appropriate in a world of nonoverlapping information. Respondents might, for example, weight government risk studies more than industry studies. We designated this approach the "naïve Bayesian" learning model.

Many of the results were consistent with the predictions of the naïve Bayesian learning model in which people weight the information based on its source and treat it as an independent source of risk information. At the most fundamental level, risk judgments increased in the expected direction with the risk assessments. Studies indicating higher risk levels boosted risk perceptions. The steepness of this relationship satisfied the usual properties of a rational learning process. The relative weights placed on the information, for example, sum to a value of approximately 1.0.

Some aspects of the behavior were not consistent with such a simplified learning model. These anomalies provide a cautionary warning for those providing risk information in situations where there is not a scientific consensus. In situations in which there are divergent risk judgments and where the identity of the parties is different, people are particularly likely to place the greatest weight on the worst case scenario. This undue emphasis on the worst case possibility is accentuated when there are different sources of risk information, as opposed to a single information source but with different risk estimates. People are particularly skeptical of low risk estimates from the polluting industry in situations in which the high risk estimate is from the government agency. This dismissal of industry risk information in this context may reflect the fact that people do not weight the industry risk information independent of the risk information context and the underlying economic incentives of the parties. When both of the risk assessments are from the industry, however, people are less likely to dismiss the industry low risk estimate.

Situations in which experts differ are consequently likely to generate alarmist responses to dimly understood risks. These reactions in turn will create public pressures for stringent regulation. Regulators as individuals may be subject to the same biases, and to the extent that they are responding to political pressures from an alarmed public, these biases will be reinforced. The result, as is documented in Viscusi (1998), is that policies often reflect a variety of conservative biases in which there is excessive regulation of imprecisely understood risks, compared to better known risks with higher mean risk values. This bias is a reflection of the same kinds of risk judgment biases found in our study.

The behavior of cigarette smokers was particularly instructive because it afforded an opportunity to assess how smokers process risk information and make risk judgments in another risk context. Controlling for other demographic characteristics, smoking status had an important influence on risk beliefs. It is noteworthy that smokers do not differ from nonsmokers by simply having lower prior probability values for the risk. There is not simply a difference in smokers' prior beliefs. Rather, they process risk information differently than do nonsmokers. Overall, there is less of a tendency for nonsmokers to place a disproportionate weight on the high risk assessments they receive.[18] Moreover, smokers are particularly likely to dismiss the low risk assessment by industry in situations in which the government is providing a higher risk value. This situation parallels many risk contexts in terms of the respective role of industry and government in providing divergent risk information estimates.

Making judgments regarding the rationality of smokers' information processing is more problematic. If the behavior of nonsmokers serves as the rationality reference point, then smokers clearly fall short through their underestimation of risks. However, nonsmokers placed a disproportionate weight on the high risk assessments and had a more exaggerated response to risk information than would be predicted by a naïve Bayesian learning model. Smokers' failure to integrate risk information in the same manner as nonsmokers is not necessarily evidence of irrationality. What is clear is that smokers are likely to process risk information in a manner that is less sensitive to the high risk estimates they receive, with the result being lower risk beliefs. This pattern of behavior for a nonsmoking risk context may explain in part why smokers believe that the risks of smoking are less than do nonsmokers.[19] Moreover, it may also help account for the greater risk-taking behavior of smokers across a variety of domains of choice.

Appendix

Sample Description

Individuals participating in the study were recruited by a professional market research firm at a mall intercept in Greensboro, North Carolina. This locale is not a university town and has demographic characteristics reflective of the U.S. population more generally (Table A1).[20] The respondents were told that they would be participating in a Duke University study of city preferences. The sample for this study (Table A1) consisted of 143 adults. The mean sample age is 35 years old. Just under half of the sample is male, and the sample has an average of 13 years of education with an income of $28,000 per year.[21] The survey was undertaken in the late summer and fall of 1993.

Summary of Survey Questions

Below, we provide a brief summary of the key sections of the survey used in this analysis. This summary indicates the survey structure and language but does not provide information on all the iterations that were used to obtain indifference because these questions varied depending on the particular respondent. The order of the risk information combinations was rotated on a random basis.

Each of the respondents focused on three of the four scenarios. In every scenario, government and industry experts agree on the exact risk in area 2, whereas the risk in area 1 was ambiguous. One scenario has a government expert and an industry expert to estimate the risk for area 1, the second scenario has only industry experts for area 1, and the final scenario has only government experts for area 1. Each subject answered two questions from each of the three scenarios for a total of six responses per subject. The following risk pairs were used randomized over the six questions: (100, 300), (200, 400), (100, 900), (10, 200), (80, 100), and (615, 715).

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[18] Speculating on the reasons for this discrepancy is beyond the scope of this paper. Do smokers discount government information because they believe the government has overstated the risks of smoking? Or do these people smoke because they systematically ignore such warnings and underestimate the risk?

[19] For detailed statistics on the lung cancer and mortality risk beliefs of smokers and nonsmokers, see Viscusi (1992b).

[20] We explore the characteristics of the sample population at this locale in Viscusi and Magat (1987) and Magat and Viscusi (1992). For example, Greensboro is not a college town and is a frequent test marketing site used by companies and government agencies to assess public responses to new products and policies.

[21] Individuals who reported themselves as black or "other" races were oversampled relative to the U.S. population. Although the demographic controls will account for many of these differences, this sample is clearly not a nationally representative random sample.

Table A1. Summary of Sample Characteristics

Variable	Mean (Standard Deviation)
Age (years)	34.832 (15.612)
Age Missing (0–1 dummy variable [d.v.])	0.049 (0.217)
Nonwhite and Other (0–1 d.v.)	0.385 (0.488)
Male (0–1 d.v.)	0.441 (0.498)
Education (years)	13.381 (2.980)
Income (in annual 1993 dollars)	28,189 (25,689)
Income Missing (1–0 d.v.)	0.133 (0.341)
Single (0–1 d.v.)	0.524 (0.501)
Smoker (0–1 d.v. of current smoking status)	0.287 (0.454)
Low Risk (per million population)	184.17 (200.62)
High Risk (per million population)	439.17 (286.82)
Sample Size	143

The Survey

Some chemical companies cause air pollution, and this air pollution can cause cancer. In other words, the factories that make chemicals can make the air unhealthy to breathe.

Suppose that there are two chemical companies, one in area 1 and one in area 2. Both of these companies cause air pollution, and their air pollution can cause cancer.

The company in area 1 is not exactly the same as the one in area 2, so the chance of getting cancer in each area is different.

As we have done before, we will ask experts to estimate the chance of getting cancer from the pollution in each area. But this time we are going to tell you who the experts are.

Some of the experts work for the government and some of the experts work for the companies that cause the pollution.

For area 1, the government expert and the company expert DO NOT AGREE. That is, the government expert thinks the risk in area 1 is different than what the company expert thinks.

A lot of research has been done in area 2, and the scientists have learned the exact risk of cancer from air pollution. The government expert and the company expert both agree on this number.

The company in area 1 is not exactly the same as the one in area 2, so the chance of getting cancer in each area is different.

As we have done before, we will ask experts to estimate the chance of getting cancer from the pollution in each area. But this time we are going to tell you who the experts are.

Some of the experts work for the government and some of the experts work for the companies that cause the pollution.

For area 1, the government expert and the company expert DO NOT AGREE. That is, the government expert thinks the risk in area 1 is different than what the company expert thinks.

A lot of research has been done in area 2, and the scientists have learned the exact risk of cancer from air pollution. The government expert and the company expert both agree on this number.

Your chance in a million of cancer	AREA 1		AREA 2
	GOVERNMENT EXPERT	COMPANY EXPERT	GOVERNMENT AND COMPANY EXPERTS AGREE
	100	300	200

If you had to make a choice, which area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

[suppose area 1 is chosen]

Your chance in a million of cancer	AREA 1		AREA 2
	GOVERNMENT EXPERT	COMPANY EXPERT	GOVERNMENT AND COMPANY EXPERTS AGREE
	100	300	200 180

YOU CHOSE AREA 1

Suppose the risk in AREA 2 was lower than before, as shown by the new number above.

If you had to make a choice, whick area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

Good! Press 0 for another question.

Your chance in a million of cancer	AREA 1		AREA 2
	COMPANY EXPERT 1	COMPANY EXPERT 2	GOVERNMENT AND INDUSTRY EXPERTS AGREE
	200	400	300

THERE IS NO GOVERNMENT INFORMATION ABOUT AREA 1.
BOTH EXPERTS IN AREA 1 WORK FOR THE CHEMICAL COMPANIES.

If you had to make a choice, which area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

[suppose area 2 is chosen]

Your chance in a million of cancer	AREA 1		AREA 2
	COMPANY EXPERT 1	COMPANY EXPERT 2	GOVERNMENT AND INDUSTRY EXPERTS AGREE
	200	400	300 330

YOU CHOSE AREA 2

Suppose the risk in AREA 2 was higher than before, as shown by the new number above.

If you had to make a choice, which area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

Good! Press 0 for another question.

Your chance in a million of cancer	AREA 1		AREA 2
	GOVERNMENT EXPERT 1	GOVERNMENT EXPERT 2	GOVERNMENT AND INDUSTRY EXPERTS AGREE
	615	735	675

THERE IS NO COMPANY INFORMATION ABOUT AREA 1.
BOTH EXPERTS IN AREA 1 WORK FOR THE GOVERNMENT.

If you had to make a choice, which area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

Your chance in a million of cancer	AREA 1		AREA 2
	GOVERNMENT EXPERT 1	GOVERNMENT EXPERT 2	GOVERNMENT AND INDUSTRY EXPERTS AGREE
	615	735	675 650

YOU CHOSE AREA 1

Suppose the risk in AREA 2 was lower than before, as shown by the new number above.

If you had to make a choice, which area would you rather live in?

1. AREA 1 2. AREA 2
3. Both areas are the same to me

Press the number that goes with your answer

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