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# ALARMIST DECISIONS WITH DIVERGENT RISK INFORMATION*

*W. Kip Viscusi*

Receipt of multiple sources of risk information ideally should foster sounder decisions under uncertainty. This paper's original survey results for environmental risks suggest that the learning process is reasonable in many respects, but it does not accord with a rational Bayesian learning model. Divergent risk assessments from different sources produce extreme violations of rationality, as there is inordinate weight on the high risk assessment. This alarmist reaction holds for both government and industry information sources. This phenomenon may account for the commonly observed phenomenon of public overreaction to highly publicised risks.

One of the most noteworthy economic events of 1996 was the public's reaction to the risk of mad-cow disease from British beef. The fear of this disease generated massive losses to the British economy. What was particularly striking about the influences generating the extreme public reaction was the fragmentary nature of the risk evidence. One scientist estimated that mad-cow disease could lead to 500 to 500,000 British deaths from Creutzfeldt–Jacob disease transmitted through cattle.[1]

How will people respond when confronted with such vague risk information? What predictions can economists offer regarding the likely response? Will people simply use the mean risk as their guide? Does the range of risk estimates matter? To what extent is it important that the different parties may offer conflicting risk judgements? This paper explores a range of such issues using original data on environmental risk beliefs.

Many traditional economic theories would offer greater reassurance than is consistent with actual behaviour. A basic tenet in economics is that more information is better.[2] Increased knowledge about the risks we face will enable us to make sounder decisions and increase our expected utility judged on the basis of the true probabilities. Unfortunately, these beneficial results of information are not always borne out in practice. New information about risks may generate alarmist actions that are not commensurate with the magnitude

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[1] See 'Mad Cows and Englishmen,' (March 30, 1996) *The Economist*, p. 25.

[2] This principle in turn is based on fundamental results in the decision analysis literature. See, for example, Pratt *et al.* (1975).

of the risks.[3] Differences in risk information and processing of it often lead the public to have quite different risk perceptions than government experts.[4]

Increasingly, we receive multiple sources of information about the risks we face. Investors in the stock market receive conflicting reports of the prospects for different investments. In the case of non-financial health risks, government agencies have placed greater reliance on risk communication efforts over the past two decades. These policies have encompassed risks in the workplace, product safety risks (e.g. pharmaceuticals and pesticides), and broader environmental hazards. Private parties, particularly industries responsible for generating the risk, often provide information as well. These risk information efforts often reflect divergent viewpoints. The American Medical Association and the US Food and Drug Administration, for example, had a sharp public disagreement over the health consequences of silicon gel breast implants.[5] Conflicting information from other sources may be influential as well, including academic studies and general commentary in the media.

A fundamental economic question is how individuals process diverse and often conflicting risk information. A substantial recent literature has begun to question the rationality of choice taking in risky situations. This literature has shown that people generally have difficulty in making choices under uncertainty. One potential context that has not been adequately considered and which is a pertinent feature of many decision contexts is the influence of diverse information sources and the potential irrationalities they may generate. Since multiple, conflicting risk reports will add an additional layer of complexity, one would expect people to have substantial difficulty in making reliable judgements in this instance. What will be of greatest interest is whether there are systematic patterns of error.

Addressing the effect of multiple risk judgements is of intense practical significance. Situations of diverse and conflicting risk information have become increasingly prevalent and are likely to increase in importance. Policymakers are placing greater reliance on individual and community involvement in environmental choices, such as the cleanup of hazardous wastes and the siting of nuclear wastes. Information provision is a key component of this process. To what extent will people utilise the governmental information and how does the presence of other information sources affect the risk communication process? Is information from multiple sources weighed in a rational manner? Is

[3] Here we will distinguish the role of additional information about risks from information that calls risks to people's attention that they were not aware of before. See Viscusi *et al.* (1987) and Samuelson and Zeckhauser (1988) for discussion of the 'reference risk' effect or 'status quo' bias, respectively. The excessive response to small risks called to people's attention found by Fischhoff *et al.* (1981) contrasts with the tendency to ignore low risks of disaster found by Kunreuther *et al.* (1978). The difference in response appears to be due in large part to the character of the information.

[4] US Supreme Court Justice Breyer (1993, pp. 20–1) notes that government and public risk assessments are often at odds. Government experts, for example, rank the number one risk in public perceptions – hazardous waste sites – as being a medium to low risk whereas the number 23 risk in the public's view – indoor air pollution – is ranked as a high risk by government experts.

[5] The American Medical Association's Council on Scientific Affairs published a report claiming that there was no convincing evidence that breast implants caused health problems, whereas the Commissioner of the Food and Drug Administration claimed that the AMA's position was 'insupportable' and that there were 20,000 reports of breast implant problems annually. See *The Washington Post*, December 1, 1993, p. A4.

information provided by the government more credible than information provided by the firm generating the risk? To what extent is this behaviour consistent with a rational Bayesian learning process? What systematic departures from rationality can be identified?

The decision context that will be considered here is that of location decisions in the presence of air pollution risks. Individuals provided with information from diverse combinations of government and industry sources will indicate their preferences with respect to potential alternatives to move to different areas posing different risks.

The implication of this study is that information provision is potentially effective but that many of the patterns are surprising. Though risk information is influential, the overall patterns of risk information processing are not fully consistent with a rational learning process. Moreover, the character of the irrationality is systematic, but nevertheless, quite subtle, as one must take into account not only the identity of the party providing the risk information but also the character of the information provided. Respondents place disproportionate weight on the high risk information presented to them in contexts in which there are multiple and conflicting sources of risk information. The net effect is tantamount to risk aversion in learning.

Section I presents the theoretical reference point, which is the standard rational learning model. In particular, it is a Bayesian learning model in which individuals process information consistent with a rational learning process and make decisions to maximise subjective expected utility. The structure of the survey is the subject of Section II. The estimation results presented in Section III imply that one should reject the extreme hypothesis that individuals do not learn. However, there is an asymmetry in the learning process that violates the usual rules of rationality and is consistent with many observed biases in actual behaviour. Respondents place the greatest weight on worst case scenarios when there is a diversity of risk information presented. Section IV concludes the paper.

## I. THE BAYESIAN LEARNING MODEL

The reference point used for testing rationality is a Bayesian expected utility model.[6] Respondents considered the choice of moving to one of two areas, each of which posed a cancer risk from air pollution. For Area 2, respondents were given full information regarding the risk S of an adverse outcome, whereas in Area 1 the risk perception $R$ is a function of the prior risk beliefs and two sets of risk information. The Bayesian aspect of the model arises below in that it is assumed that a rational Bayesian learning process governs the formation of the $R$ and $S$ values. The respondents' task was to equate the Area 2 lottery with the known risk $S$ to the Area 1 lottery with the risk $R$ that was the subject of the risk communication effort. The utility functions for the two possible states and for each pair of lotteries is the same because each lottery offers the same set of possible binary outcomes. All that varies is information pertaining to the chance that the unfavourable state will occur.

[6] The effect of single information sources in a Bayesian context is explored using a different survey in Viscusi and Magat (1992).

Let $U^1(Y)$ denote the utility of being healthy and having wealth $Y$, and let $U^2(Y)$ denote the utility of having money $Y$ after an adverse health outcome (where $U^1(Y) > U^2(Y)$, $U^1_x(X) > U^2_x(X)$, and $U^1_{xx}$, $U^2_{xx} \leqslant 0$). The experiment equates the expected utility in both areas, or

$$(1-R)\,U^1(Y)+RU^2(Y) = (1-S)\,U^1(Y)+SU^2(Y), \tag{1}$$

which is simply

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

Thus, the utility functions drop out as the task reduces to equating an imprecisely assessed probability to one for which there is expert consensus.

The Bayesian model is related to this formulation in that the subjective probability $R$ based on two diverse sets of information will be equated to the precisely understood probability $S$ for which full information is provided. The study design consequently finds the precisely understood risk $S$ that is tantamount to the uncertain risk $R$. The probability $S$ is a quantitative probability variable that serves the role of calibrating the lottery with the subjective probability $R$ in a manner that is equivalent to a reference lottery with known probability $S$. Within the context of choice problems in which there is no additional opportunity for learning and changing decisions, one should treat an unknown risk as being equivalent to a certain probability at the mean of the distribution. This is the standard Bayesian perspective for treating objective and subjective probabilities articulated by Raiffa (1968) and others. The value of $R$ is not observable, but the study will have data on information presented about Area 1 and the demographic characteristics likely to affect prior beliefs about the Area 1 risk.

Respondents received information from government and/or industry scientists. The following combinations of information sources pertaining to the risks in Area 1 were included: government–government, industry–industry, government–industry, and industry–government. The risk context is that of cancer due to air pollution generated by a chemical plant, where the industry scientists are hired by the polluting firm. In conjunction with their prior risk beliefs, respondents form their assessment of the risk $R$.

For concreteness, we will employ the Beta distribution of probabilities, which can assume a wide variety of skewed and symmetric shapes and is ideally suited to analysing Bernoulli-type processes such as this.[7] The Beta distribution is also simple to use in calculating the mean $R$ of the subjective probability distribution. In particular, $R$ is simply a linear weighted average of the risks associated with one's prior beliefs and each new source of information, where the weights represent the proportional share of the information content accorded to each information source.

The distribution will be parameterised in the following manner. Let $q$ be the prior risk assessment, and let $\gamma$ be its associated precision, i.e. the individual acts as if the information is equivalent to observing $\gamma$ draws of balls from a Bernoulli urn, where a fraction $q$ of these draws indicate the adverse outcome.

[7] See Pratt *et al.* (1975), for further discussion of the properties of the Beta distribution.

Similarly, the source of the low risk estimate provided in the survey indicates a risk $r$ (given in the survey) with an associated precision $\xi$ based on the identity of the risk information provided and how the individual processes the risk information. The associated risk and precision of the high risk information are given by $r^*$ and $\xi^*$. The parameter values are restricted to ensure that the probabilities are well-behaved: $0 \leqslant q$, $r$, $r^* \leqslant 1$ and $\gamma$, $\xi$, and $\xi^* \geqslant 0$. Information that has no informational content has an associated precision of zero, whereas information that is treated as being fully informative is treated as if it has an infinite weight.

The hypothetical experiment underlying this model is that the individual has undertaken three sets of independent draws from a Bernoulli urn to form the risk judgement: $\gamma$ draws to form the prior, $\xi$ draws to form the low risk assessment, and $\xi^*$ draws to form the high risk assessment. The nature of this learning process is quite simple as each set of experts, in effect, is assumed to be making different independent draws from a Bernoulli urn.

One key implicit assumption is that the sets of information are assumed to be non-overlapping. Thus, the company and the government are not making different risk judgements based on the same body of data or data that is shared to some extent. Zeckhauser (1971) models the overlapping information case and shows that the mean risk is characterised by an equation very similar to the model used here except for an adjustment for the overlapping information.[8]

Another complication is that in actual risk contexts there may be multiple sources, not just two. The clustering of the information around a common risk estimate may lead people to discount the outlier. For the experiment considered here there are only two information readings so that this concern should not enter. In addition, the orders of magnitude of the risk information provided are similar and in a reasonable range so that respondents should not dismiss the risk assessments as being implausible based on their prior knowledge. That might, for example, be the case if the stated air pollution risk was comparable to that of cigarette smoking, which would lead respondents to dismiss the risk judgement. If that concern were pertinent, it would be reflected in a lower estimated weight on the risk information provided. Thus, the level of risk probabilities could affect the information weights $\xi$ and $\xi^*$. Since the study used realistic probabilities in all scenarios, it is assumed that this complication is not a factor.

A final practical concern pertains to the design of economic structures to elicit the honest provision of information. Theoretical explorations, such as d'Aspremont and Gérard-Varet (1979) and Johnson *et al.* (1990), have

[8] In particular, suppose that there is no prior risk information but only the $\xi$ and $\xi^*$ draws for which $m$ are overlapping. Then for the normal distribution case, Zeckhauser (1971) shows that in terms of our notation the analog of (3) for the value of the mean risk is

$$R = \frac{\xi - m}{\xi + \xi^* - 2m} r + \frac{\xi^* - m}{\xi + \xi^* - 2m} r^*.$$

In this formulation, the weighted average of the mean risks is still the matter of concern, but the weights represent the amount of information that is unique to each of the two information sources. The principal change for the overlapping information case is the interpretation of the coefficients of $r$ and $r^*$ in the subsequent regressions.

indicated that payment mechanisms can be designed to foster accurate information provision. These incentive issues will not be of explicit concern here, but to the extent that respondents believe that companies have less of an incentive to provide honest risk judgements than a government agency, they will place a lower weight on such information. In actual informational contexts, the interests of those revealing the risk information, such as its relationship to potential liability, may be an important concern.

The respondent's posterior risk perception $R$ after reviewing the information is a linear weight average of each of the risk perception components, or

$$R = \frac{\gamma}{\gamma+\xi+\xi^*}q + \frac{\xi}{\gamma+\xi+\xi^*}r + \frac{\xi^*}{\gamma+\xi+\xi^*}r^*, \tag{3}$$

or the risk assessment is the fraction of the informational content for that component of risk beliefs multiplied by the associated risk level, summed over all three components.

Consider the following numerical example using the risk information for one of the survey scenarios. Suppose individuals assessed a prior risk as 200 cancer cases per million and received a government report indicating risk of 100 cases per million and a company report indicating a risk of 300 cases per million, respectively. Let the weight on the prior beliefs be tantamount to 100 draws from an urn, the weight on each government report be 200 draws, and the weight on the private report be 300 draws. Then the posterior assessed risk will be

$$\begin{aligned} R &= \frac{100}{100+200+300}(200\times 10^{-6}) + \frac{200}{100+200+300}(100\times 10^{-6}) \\ &\quad + \frac{300}{100+200+300}(300\times 10^{-6}) \\ &= 216.6\times 10^{-6}. \end{aligned} \tag{4}$$

The posterior risk is a simple linear weight average of the individual risk levels, where the weights are the fraction of the informational content associated with each information source.

The value of $R$ is bounded by 0 and 1. Each of the three components of $R$ is similarly constrained. The empirical analysis below will explicitly estimate the relative informational weights on $r$ and $r^*$, where these weights are each non-negative and

$$0 \leqslant \frac{\xi}{\gamma+\xi+\xi^*} + \frac{\xi^*}{\gamma+\xi+\xi^*} \leqslant 1. \tag{5}$$

In the case where informational content is symmetric, the weights are equal, and if also the prior has no informational content (i.e. $\gamma = 0$) these weights will equal 0.5.

People could respond to risk information in an irrational manner that some might view as alarmist. For example, the weights on the information indicated in (4) could sum to more than 1.0. Examination of that possibility was the focus of Viscusi and Magat (1992), who did not find significant evidence of such alarmist behaviour. In that analysis, respondents considered divergent risk assessments from a single source. Here the emphasis will be on alarmist reactions of a different sort based on the character of this study. Rather than being concerned with the total sum of the information weights, the focus will be on the relative weights placed on the low risk and high risk information. In particular, do individuals pay systematically greater attention to the high risk information irrespective of its source? Fearing the worst when confronted with divergent risk judgements is a form of alarmist behaviour in that respondents do not treat the information based on its credibility but place undue emphasis on forecasts of worst case outcomes.

Let $g$ denote government information provision, where the information source affects the low and high risk information parameters, but not the prior. The value of the risk perception $R(g,g)$ with both low and high risk information provided by the government is

$$R(g,g) = \frac{\gamma}{\gamma+2\xi_g} q + \frac{\xi_g}{\gamma+2\xi_g} r + \frac{\xi_g}{\gamma+2\xi_g} r^*, \tag{6}$$

or in a form that will facilitate later comparisons,

$$R(g,g) = P(g,g)\, q + L(g,g)\, r + H(g,g)\, r^*, \tag{7}$$

where the risk perception is a weighted sum of the prior risk $q$, the low risk $r$, and the high risk $r^*$, where the weights are the associated fraction $P(g,g)$ of the informational content for the prior, and the fraction $L(g,g)$ for the low risk and $H(g,g)$ for the high risk.

The industry–industry information provision case has an analogous definition. Denoting industry by $i$,

$$R(i,i) = \frac{\gamma}{\gamma+2\xi_i} q + \frac{\xi_i}{\gamma+2\xi_i} r + \frac{\xi_i}{\gamma+2\xi_i} r^*, \tag{8}$$

or
$$R(i,i) = P(i,i)\, q + L(i,i)\, r + H(i,i)\, r^*. \tag{9}$$

If the government provides the low risk information and the industry provides the high risk information, $R(g,i)$ is given by

$$R(g,i) = \frac{\gamma}{\gamma+\xi_q+\xi_i} q + \frac{\xi_g}{\gamma+\xi_g+\xi_i} r + \frac{\xi_i}{\gamma+\xi_g+\xi_i} r^*, \tag{10}$$

or
$$R(g,i) = P(g,i)\, q + L(g,i)\, r + H(g,i)\, r^*. \tag{11}$$

Similarly, if the industry provides the low risk information and the government provides the high risk information, $R(i,g)$ is given by

$$R(i,g) = \frac{\gamma}{\gamma+\xi_i+\xi_g} q + \frac{\xi_i}{\gamma+\xi_i+\xi_g} r + \frac{\xi_g}{\gamma+\xi_i+\xi_g} r^*, \tag{12}$$

or
$$R(i,g) = P(i,g)\, q + L(i,g)\, r + H(i,g)\, r^*. \tag{13}$$

A fundamental assumption of the analysis is that the respondents associate an information content to a risk finding depending only on its source, not on the source coupled with the findings. An alternative possibility might, for example, be that people will believe that studies that found higher risk values were the result of more sophisticated research efforts. If that possibility were true the $H(\cdot,\cdot)$ values would all exceed the $L(\cdot,\cdot)$ values. As the empirical results below will show, however, the greatest disparity in the $H(\cdot,\cdot)$ and $L(\cdot,\cdot)$ views is when there is a disparity in the risk information sources, which is a more complex phenomenon.

A primary focus of the empirical analysis will be on the various $L(\cdot,\cdot)$ and $H(\cdot,\cdot)$ values, which will be related in the following ways given their underlying definitions:

$$L(g,g) = H(g,g), \tag{14}$$

$$L(i,i) = H(i,i), \tag{15}$$

$$L(g,i) = H(i,g), \tag{16}$$

and

$$H(g,i) = L(i,g). \tag{17}$$

If the informational content $\xi_i$ and $\xi_g$ are equal, then

$$L(\cdot,\cdot) = H(\cdot,\cdot) \tag{18}$$

for all information combinations. This might be termed the naive Bayesian model.

The information credibility of the two parties may differ. One might expect information from the government to be more persuasive than that from a potential liable firm (i.e. $\xi_g > \xi_i$), but this need not be the case for learning to be rational. If the government information is more credible, then the relative informational weights will satisfy.

$$L(g,i) > L(g,g) > L(i,i) > L(i,g), \tag{19}$$

and

$$H(i,g) > H(g,g) > H(i,i) > H(g,i). \tag{20}$$

Similarly, if the industry information is more credible, then these conditions are reversed, or

$$L(i,g) > L(i,i) > L(g,g) > L(g,i), \tag{21}$$

and

$$H(g,i) > H(i,i) > H(g,g) > H(i,g). \tag{22}$$

These relationships will be tested explicitly below.

Much of the empirical work will be directed at tests of the naive Bayesian model, which will be rejected at least in part. One might hypothesise two possible forms of irrational behaviour to be explored in this context. The first possibility might be termed risk aversion in learning.[9] Whenever people consider differing risk information $r$ and $r^*$ that is equally credible, the net effect on perceptions will be greater than the average of the two risk values would have suggested.

A potential deviation from the Bayesian model predictions is that people may treat conflicting risk judgements differently when there is more than one information source. Instead of placing an informational weight such as $\xi_g$ on government information and $\xi_i$ on industry risk information, these weights might shift when both sources present information. People exhibit risk aversion

[9] This effect parallels other types of risk aversion phenomena, such as risk aversion in regret. See Starmer and Sugden (1989).

in learning when facing situations of conflicting information, particularly when there are different sources and, possibly, different risk study practices. This aspect of the results leads to the second, more refined hypothesis is that risk aversion in learning is most influential in the presence of differing information sources. The net effect of $r$ and $r^*$ on risk beliefs is greater than their average (i.e. the weight on $r^*$ is greater than that on $r$) when different parties are responsible for the differing risk judgements. People fear the worst and place greater relative weight on worst case scenarios whenever different experts are in conflict, irrespective of their identity.

## II. THE SURVEY APPROACH

The 143 adult participants in the study took a survey that was administered through an interactive computer program. The interactive program approach offers several advantages. First, the program presents each respondent the questions in an identical manner so that there is no bias created because of the presentation by the particular survey personnel. Secondly, subjects may be more willing to give truthful and honest responses to a computer than they are to an in-person interviewer. For example, there were fewer missing values for answers to such sensitive questions as individual income than in face-to-face interviews. Thirdly, the character of the survey involved a sequence of interactions in which individuals made pairwise comparisons between the risky situations until indifference was reached. The computer program was designed to calculate alternatives presented to the respondents taking into account the respondent's indicated preferences to earlier questions, thus facilitating the process of identifying the equilibrating risk situations.

The specific risk context considered was that of air pollution emissions from chemical factories that posed a risk of cancer.[10] Individuals faced a choice of living in Area 1 or Area 2.[11] Area 2 entails no uncertainty, as government and company experts agree on the risks, and 'scientists have learned the exact risk of cancer from air pollution' in Area 2.

Respondents considered situations involving information from two parties regarding the risks $r$ and $r^*$ in Area 1: (1) information provided by two different government studies ($g$–$g$). (2) information provided by two industry studies ($i$–$i$), (3) low risk information provided by an industry study and high risk information from a government study ($i$–$g$), and (4) low risk information provided by a government study and high risk information from an industry study ($g$–$i$). In each case, the indicated order reflects the level of the risk involved. Thus, for the $i$–$g$ scenario, the low risk information is provided by industry, and the high risk information is provided by government. The reversal of this combination tests for whether having the government providing the low risk information and the industry providing the high risk information generates a different risk effect.

[10] This question appeared in the survey after respondents already had practice in answering similar risk comparisons for other contexts. However, this is the first context in which the identity of the risk information provided to the respondent was indicated. Moreover, it was the first context involving air pollution.

[11] Respondents were told that each of these areas posed a lower risk than the current area in which they lived to prevent any unwillingness to consider a potential move.

To provide risk variation, six different risk combinations $r$ and $r^*$ for the cancer case values per million residents in Area 1 are utilised: (100, 300), (200, 400), (100, 900), (10, 200), (80, 100), and (615, 735). By focusing on the numerator of these estimates and having an identical denominator, subjects were better able to deal with risk data than if they had been given information such as a 0·0001 risk of cancer.[12] These six risk pairs are utilised for all different combinations of risk information provided to the respondents.

## III. EMPIRICAL ESTIMATES

Since respondents faced several risk questions, it is possible to eliminate the role of fixed person-specific differences that affect the level of risk perceptions by using a fixed effects estimation approach. Thus, the estimation takes the form,

$$S = \alpha_i + \psi r + \psi^* r^* + \epsilon, \tag{23}$$

where $\alpha_i$ is a person-specific intercept term, $\epsilon$ is a random error term, and $\psi$ and $\psi^*$ are the fractions of the total information accounted for by the low and high risk estimates. All fixed person-specific differences such as income, race, smoking status, and education consequently will be taken into account to the extent that these values enter additively. This formulation factors out all person-specific differences in prior beliefs from the analysis.

Table 1 reports the fixed effects estimation results. Except in the $g$–$g$ case, the point estimates of the weights on the high risk information are greater than the low risk weights. Situations of divergent risk judgements by different parties lead to larger weights on the high risk assessment, where these differences are statistically significant in the $g$–$i$ case.[13] For situations in which the source of the risk information is identical, the weights are not significantly different.[14] The most striking other difference is that $H(g,i)$ is significantly greater than $L(i,g)$, and $L(g,i)$ is significantly different from $H(i,g)$.[15] Many other parameter differences do not pass the usual tests of statistical significance.[16]

Respondents treat the high risk information as being more informative. This pattern is borne especially in the $g$–$i$ and $i$–$g$ cases in which there are different information sources. This predilection for treating worst case scenarios as being more consequential is consistent with observed biases in government risk regulation programmes as well, as 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.[17] Individual respondents display a similar orientation in that the fear of

[12] The advantage of this approach is discussed further in Viscusi and Magat (1987) and Magat and Viscusi (1992).

[13] The test F value for $L(g,i) = H(g,i)$ is 8·52 and the critical $F_{0\cdot05}(1,128)$ value is 3·92. Similarly, the test F value for $L(i,g) = H(i,g) = 2\cdot94$, with a critical $F_{0\cdot05}$ (1, 103) value = 3·94.

[14] In particular, $L(g,g) = H(g,g)$ has a test statistic of 1·002 and a critical $F_{0\cdot05}$ (1, 140) value = 3·90, and $L(i,i) = H(i,i)$ has a test F value of 1·771 and a critical $F_{0\cdot05}(1,140)$ value = 3·90.

[15] The test F value is 5·410 and the critical $F_{0\cdot05}$ (1, 232) value = 3·89 for $H(g,i) = L(i,g)$, for $L(g,i) = H(g,i)$ the F test statistic is 10·086, and the critical $F_{0\cdot05}$ (1, 232) = 3·89.

[16] In particular, $H(g,g) = H(i,i)$ has a test F value of 1·209, $L(g,g) = L(i,i)$ has an F value of 1·549, $L(g,i) = L(i,g)$ has a test value of 0·301, and $H(g,i) = H(i,g)$ has a test value of 1·814, none of which are above the critical $F_{0\cdot05}$ values.

[17] See Nichols and Zeckhauser (1986) and Viscusi (1992).

Table 1

*Selected Coefficients for Risk Perception Regressions with Fixed Effects*

Coefficients (standard errors) [Heteroskedasticity – adjusted standard errors]

| | Government–government | Industry–industry | Government–industry | Industry–government |
|---|---|---|---|---|
| Low risk | 0·556* | 0·532* | 0·365* | 0·374* |
| | (0·067) | (0·068) | (0·092) | (0·087) |
| | [0·066] | [0·070] | [0·043] | [0·079] |
| High risk | 0·472* | 0·650* | 0·654* | 0·553* |
| | (0·092) | (0·104) | (0·043) | (0·041) |
| | [0·089] | [0·086] | [0·060] | [0·060] |
| $\bar{R}^2$ | 0·333 | 0·339 | 0·652 | 0·707 |
| $N$ | 143 | 143 | 131 | 106 |

* Asterisks denote coefficients that are statistically significant at the 5% level, one-tailed test, using the White (1980) heteroskedasticity-adjusted standard errors.

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.[18] Such risk aversion in learning appears more prevalent when different parties are the sources of the conflicting judgements. This phenomenon is, however, independent of the shape of individual preferences and the presence of risk aversion for changes in wealth.

Table 2 summarises the various point estimates and their relationship to the various theoretical hypotheses. The hypothesis of statistically symmetric weights on the information is not borne out, where the two significant differences appear in the two cases of differing information sources designated 3 and 4 in Table 2. However, the greater credibility of one of the two information sources does not account for these results since no consistent pattern is observed in the bottom sections of Table 2. The difficulty is that symmetry is not violated because a particular information source's credibility is more consequential. Rather, it is the divergence of judgements from different sources that largely accounts for the differing information weights.

Notwithstanding these results, there is much in the empirical results that is favourable for a constructive role of individual learning. Both low and high risk estimates influence people's perception of the risk. Risk beliefs are not rigid and immutable. The theoretical prediction is that the information weights will sum to 1·0 in the case of rational learning where the experimental information is all that is consequential. The weights summed to values ranging from 0·93 for the *i–g* case to 1·18 for the *i–i* case, and were almost identical to 1·0 in the other two instances.

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

Table 2

*Summary of Parameter Relationship Tests of Bayesian Learning Model*

| |
|---|
| Symmetry hypotheses |
| (1) $L(g,g) = H(g,g)$? from equation (14) |
| $0{\cdot}56 = 0{\cdot}47$ |
| (2) $L(i,i) = H(i,i)$? from equation (15) |
| $0{\cdot}53 = 0{\cdot}65$ |
| (3) $L(g,i) = H(i,g)$? from equation (16) |
| $0{\cdot}37 = 0{\cdot}65$ |
| (4) $L(i,g) = H(g,i)$? from equation (17) |
| $0{\cdot}37 = 0{\cdot}55$ |
| *Government information more credible* |
| (5) $L(g,i) > L(g,g) > L(i,i) > L(i,g)$? from equation (19) |
| $0{\cdot}33 > 0{\cdot}56 > 0{\cdot}53 > 0{\cdot}37$ |
| (6) $H(i,g) > H(g,g) > H(i,i) > H(g,i)$? from equation (20) |
| $0{\cdot}55 > 0{\cdot}47 > 0{\cdot}65 > 0{\cdot}65$ |
| Industry information more credible |
| (7) $L(i,g) > L(i,i) > L(g,g) > L(g,i)$? from equation (21) |
| $0{\cdot}37 > 0{\cdot}53 > 0{\cdot}56 > 0{\cdot}37$ |
| (8) $H(g,i) > H(i,i) > H(g,g) > H(i,g)$? from equation (22) |
| $0{\cdot}65 > 0{\cdot}65 > 0{\cdot}47 > 0{\cdot}55$ |

The main difficulty is that there is a tendency to discard the low risk judgement, giving it a weight of 0·37, and to place an excessive weight on the high risk judgement in situations in which two information sources disagree. Rather than weight the judgements in a balanced manner, respondents veer toward the worst case judgement when there are two differing sources that disagree. This phenomenon occurred whether the high risk estimator was the government or the industry. Perhaps somewhat surprisingly, fear of the worst case scenario is not as consequential a factor when a single risk source presents differing risk estimates.

## IV. CONCLUSION

Individual learning contexts in which diverse risk information is characterised by an irrational asymmetry; respondents overweight the value of the high risk judgement. This phenomenon may account for the observed overreaction to highly publicised risks. The reference point used was a standard Bayesian learning model in which people update their beliefs in a rational manner using the information provided to them. This model permits a considerable degree of discretion with respect to the way in which the information is weighted and processed. Individuals can choose to ignore information presented to them and still pass a rationality test, though we might wish that they had been more responsive. It is also potentially rational to place a substantial weight on information presented by the government or the industry, where these weights may not be identical. The theoretical reference point imposed no restrictions in terms of the credibility that respondents might attach to industry or government risk information, only that these weights be consistent.

Overall, the respondents placed considerable weight on the risk information provided to them. In particular, the relative informational weights on the two sources of risk information about the air pollution cancer risks summed to an average of approximately 1·0. Respondents regarded the risk information presented as being much more informative than their priors.

For all respondents, there was a fundamental inconsistency in the character of the behaviour as compared with the standard Bayesian model. Individuals may reasonably place different information weights on different sources of information. However, the greater weight on the high risk information in situations of competing information sources could not be reconciled with differential weights on the informational source. This behaviour led to the rejection of several predictions of standard variants of the naive Bayesian model.

Although people do learn, they devote excessive attention to the worst case scenarios. The alarmist responses to risk information that often characterise the public's behaviour in actual risk contexts were consequently reflected in these results. It is not simply the case that individuals happen to believe that the information source that provided the high risk information in a particular risk context is more credible. The credibility weight on the source varies depending on whether the source is providing high risk or low risk information and on the other party providing information.

In theory, the experimental situations considered here represent a straightforward generalisation of standard learning models. Actual situations with multiple information sources are much more complex. However, even within the context of two pieces of risk information, decisions appear to be distorted when there is more than one information source. The diversity of risk information introduced patterns that were altogether inconsistent with a conventional Bayesian learning framework. When differing risk judgements were offered by different parties, the high risk assessment was accorded a dominant role. This predilection toward alarmist responses and excessive weighting of the worst case scenario is consistent with frequently observed behaviour in which individuals respond dramatically to fragmentary evidence of potential risks. Moreover, the practice of government agencies to base risk regulation on upper bounds of 95% confidence limits and, in some cases, the maximum risk assessment for chemical exposures may reflect the policy implementation of this class of perceptional biases.

These results also suggest that government policymakers should be cautious in providing multiple risk judgements. Consensus risk estimates are more likely to be processed in a manner that reflects the underlying risk values being communicated. Diverse risk evidence is more prone to risk overestimation than provision of information on which the risk experts agree. There may be considerable advantage to focusing the risk communication effort on the mean risk not the risk assessment range. Particular care should be taken with respect to the worst case scenarios. In practice, the distortions in risk beliefs due to the worst case scenarios may be even greater than found here since these experiments presented low risk and high risk estimates symmetrically. In contrast, the media and advocacy groups often highlight the worst case scenarios, which will tend to intensify the kinds of biases observed here.

These findings do not hinge on the health character of the risk since the utility functions dropped out of the structure of the model. One would expect there to be similar anomalies in other informational contexts, whether it be the prospects of the stock market or the risk posed by natural disasters. Conflicting risk judgements from different sources complicate decision problems that people find difficult to solve consistently even under much simpler conditions.

More generally, these results do not provide great comfort to economists who hypothesise that decisions will become more rational as we acquire more information to make these decisions. This research took as the reference point the situation in which respondents attached a weight to risk information depending only on its source, not on the nature of the findings or the other information provided. Within the context of this model, people do not appear to refine their risk beliefs in a rational manner that ultimately will converge on an accurate risk assessment after being provided with successive sets of information reflective of the underlying risks. Instead, they process this information in a much more inconsistent fashion. Judgements made in the presence of conflicting risk information when there is a diversity of viewpoints appear to be particularly prone to error.

*Harvard Law School*

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