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EFFICIENT REGULATION OF ENVIRONMENTAL HEALTH RISKS*

ERIK LICHTENBERG AND DAVID ZILBERMAN

This paper introduces a decision framework for regulating environmental health risks which incorporates the characteristic uncertainty about the dissemination and toxicological impacts of environmental contaminants and the behavioral restrictions commonly encountered. Analysis indicates that increases in uncontrollable uncertainty will increase emphasis on average performance, that more potent or less controllable risks will be regulated more stringently and that increasing aversion to uncertainty may result in poorer average performance. The paper also develops an alternative measure for valuing risk of loss of life taking into account uncertainty about health risk generation processes.

The health risks posed by environmental contaminants have emerged in recent years as a critical concern for public policy. Determining appropriate policy responses has proved difficult, largely because of the considerable uncertainty typically surrounding these risks and the processes producing them (see, for instance, Lave [1982]). Thus, regulatory decisions involve not just managing risk, but managing risk compounded by uncertainty. Furthermore, it is evident that decision makers—and the general public—are quite sensitive about the relatively unlikely prospects that these risks are large, implying a need for decision methods that incorporate uncertainty explicitly in a practical manner.

This paper introduces such a methodology. Its essence is the application of a safety rule decision criterion to a probabalistic model of risk generation. This approach has several key strengths. First, it is practical. It is essentially an extension of Baumol and Oates's [1971] standards-and-charges approach to environmental regulation to the case of uncertainty. Moreover, it is designed for use with the kinds of risk assessment models produced for regulatory purposes. Second, it is equivalent to the use of significance levels for statistical decision making. Because this classical statistics procedure is used by economists and scientists from most other disciplines, it is more amenable to the interdisciplinary cooperation required for environmental health regulation. Third, it corresponds closely to the terms of much of the relevant legislation, which charges regulators with balancing cost against adequate protection

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of public health within a sufficient margin of safety. This applies especially to statutes enacted or amended more recently such as the Federal Insecticide, Fungicide and Rodenticide Act; the Toxic Substances Control Act; and the Safe Drinking Water Act. It is also to be expected as a matter of practical politics that some balancing of risk against cost will enter into regulatory decision making even under statutes specifically forbidding it, such as the Clean Air and Clean Water Acts. Therefore, the analysis of the implications of this approach has positive content as a description of actual regulatory practice, as was recognized by Beavis and Walker [1983].

The paper proceeds as follows. First, it introduces a risk assessment model, and adapts it for decision making under uncertainty. It then investigates the two main types of problems involved in regulation: (1) determining the appropriate regulatory strategy, including the division between information gathering and other activities; and (2) allocating funds among alternative information-generating activities. Finally, a measure of the value of risk reduction is developed and its properties are examined.

I. A Model of Quantitative Risk Assessment

It will be useful to begin by clarifying some terminology, since the terms "risk" and "uncertainty" are used somewhat differently in a health context than is traditional in economics. By risk we mean the probability that an individual selected randomly from a population contracts an adverse health effect (i.e., the probability of mortality or morbidity). The relationship between risk and the variables that generate it is not known with certainty, so that the health risk estimates used for policy evaluation are subject to error. The term uncertainty will be used here as a measure of the magnitude of this error.

The chain of causality leading from environmental contamination to a set of specific hazards to human health is typically broken down into a series of subprocesses, each of which can be characterized in terms of a set of parameters to be estimated. This paper will restrict its attention to the regulatory risk assessment model proposed by Crouch and Wilson [1981] which represents the overall health risk as a multiplicative combination of parameters describing the relevant environmental conditions and demographic characteristics. This model is applicable to a broad variety of health risk problems. For instance, one can model the chronic health risks arising from the use of contaminated drinking water as the product

of the level of contamination introduced into the environment, the rate at which the contaminant enters the water supply, rates of water consumption, and dose-response rates; air-pollution-induced illness as a product of emission rates, air intake rates, and dose-response rates; and pesticide residue poisonings as a product of pesticide application levels, oxidation rates, dermal absorption rates, and dose-response rates. An additional attraction of the multiplicative form is that it constitutes a good (first-order) approximation to any of the risk assessment models in common usage at the low exposure levels characteristic of environmental health problems.

It will be convenient to work with the log risk, denoted Y. Because it is a monotone increasing function of the health risk, this transformation will not alter the qualitative conclusions obtained. Let $X_i, i = 1, \ldots, n$ denote the log of the ith parameter. Then the log of the overall risk is $Y = \Sigma_{i-1}^{n} X_i$. Assume also that the original parameters have a joint lognormal distribution, so that the log parameters, $X_i, i = 1, \ldots, n$ have a joint normal distribution. Let X_i have mean M_i and variance S_i^2 and X_i and X_j have covariance $r_{ij}S_iS_j$. Then the mean and variance of the log risk are

$$(1) \qquad EY = \sum_{i-1}^{n} M_i, \quad V(Y) = S_Y^2 = \sum_{i=1}^{n} S_i^2 + \sum_{i \neq j} r_{ij}S_iS_j.$$

II. Risk Management Using Safety Rules

The safety rule approach to regulation seeks to limit to some small amount the frequency of violations of a predetermined standard. In the context of health risk regulation, this goal can be expressed as ensuring that the incidence of the relevant adverse health effect (here the log health risk Y), exceeds some maximum allowable level, denoted Y_0, no more than a fraction of the time $1 - P$, implying that the problem of cost-efficient health risk regulation is essentially a variant of Kataoka's [1963] safety-fixed model. Denoting the social cost of regulation by R, this decision problem can be expressed as one of choosing a set of policies to minimize R subject to the constraint that $Pr\{Y \geq Y_0\} \leq 1 - P$.

Let $Y(P)$ denote the level of log risk exceeded with probability $1 - P$ and $F(P)$ denote the value of the standard normal which is exceeded with probability $1 - P$. For a normally distributed random variable, $F(P) = [Y(P) - EY]/S_Y$. Therefore,

$$(2) \quad Y(P) = EY + F(P)S_Y = \sum_{i=1}^{n} M_i + F(P)\left[\sum_{i=1}^{n} S_i^2 + \sum_{i \neq j} r_{ij}S_iS_j\right]^{1/2}.$$

The constraint that the probability of the log health risk exceeding the maximum allowable level Y_0 be no greater than $1 - P$ is then equivalent to the condition that $Y(P)$ not exceed Y_0; i.e., $Y(P) \leq Y_0$ or

$$(3) \qquad Y(P) = \sum_{i=1}^{n} M_i + F(P)\left[\sum_{i=1}^{n} S_i^2 + \sum_{i \neq j} r_{ij} S_i S_j\right]^{1/2} \leq Y_0.$$

This formalization raises two points worth noting. First, regulatory decisions are based on two parameters: maximum allowable log risk (Y_0) and margin of safety (P). These parameters are relatively easy for regulators to grasp conceptually and to determine intuitively. In addition, they tend to be the numbers around which public debate centers, so that regulators can be guided at least in part by the political process in making this type of decision. Second, this formulation expresses the log risk as a combination of mean risk and uncertainty, where uncertainty is weighted by the constant $F(P)$. The latter can be interpreted as an expression of regulators' aversion to uncertainty, the counterpart of the traditional notion of risk aversion in this context: setting $P = \frac{1}{2}$ ($F(P) = 0$) is essentially the equivalent of neutrality with respect to log risk, while the higher P is (i.e., the lower is the probability of exceeding a given risk level), the larger $F(P)$, is and hence the greater is the weight placed on uncertainty.

III. The General Character of Agency Decisions

Suppose that the regulatory agency has available n different policy instruments and that the extent to which each is applied can vary and is measured as an increasing function of social cost, which includes welfare losses imposed on consumers and producers and government expenditures. Let R_i be the total social cost of the ith regulatory activity, $i = 1, \ldots, m$. Each activity may affect both the mean and the variance of the n parameters of the risk-generating process. Both the mean and standard deviation of each parameter are assumed to be non-increasing in R, implying that $\partial M_i/\partial R_k \leq 0$, $\partial S_i/\partial R_k \leq 0$ for all $i = 1, \ldots, n$ and $k = 1, \ldots, m$. The social cost of regulation is also assumed to exhibit diminishing marginal productivity, so that $\partial^2 M_i/\partial R_k^2 \geq 0$ and $\partial^2 S_i/\partial R_k^2 \geq 0$ for all $i = 1, \ldots, n$ and $k = 1, \ldots, m$. The agency's decision problem is to minimize the total cost of meeting a given safety level. The dual of this problem, which may be relevant in some situations, is to minimize the health risk occurring with a given probability given a fixed agency budget.

The primal problem can be expressed as

$$\max_{R} \; -\sum_{i=1}^{m} R_k, \tag{4}$$

subject to the constraint (3).

Let $t_i = (S_i^2 + \Sigma_{i=1}^{n} r_{ij} S_i S_j)/S_Y^2 (j \neq i)$ represent the share of uncertainty about the ith parameter in total uncertainty and $e_{ik} = (R_k/S_i)\,(\partial S_i/\partial R_k)$ be the elasticity of the standard deviation of the ith parameter with respect to the kth action. The necessary conditions for minimum social cost can be written as the m equations:

$$-\sum_{i=1}^{n} \frac{\partial M_i}{\partial R_k} + \left[\frac{F(P) S_Y}{R_k}\right] t_i e_{ik} \leq \frac{1}{g} \tag{5}$$

plus the constraint (3), where g represents the shadow price of this constraint. The sufficient conditions for optimization are satisfied as long as expenditure exhibits diminishing marginal productivity in reducing both mean risk and uncertainty about risk.

Equation (5) indicates that each policy has two kinds of effect on risk: a mean effect ($\Sigma_{i=1}^{n}\, \partial M_i/\partial R_k$) reflecting the reduction in mean risk and an uncertainty effect ($[F(P)S_Y/R_k]\, \Sigma_{i=1}^{n}\, t_i e_{ik}$) reflecting the reduction in uncertainty about risk. It is evident from equation (5) that the efficient mix of regulatory policies will be a portfolio of activities, some of which have a relative advantage in reducing mean risk (have relatively large mean effects) and others, in reducing uncertainty about risk (have relatively large uncertainty effects). Some activities specialize in reducing either mean risk or uncertainty about risk. For example, information-gathering activities like data collection and methodological improvements in estimating exposures or physiological responses tend to have significant uncertainty effects but negligible mean effects and can thus be viewed as policies specializing in uncertainty reduction.

Further investigation of the characteristics of these efficient policy portfolios requires the use of simpler models and is taken up in the following section.

IV. Efficient Regulatory Strategy

Consider perhaps the simplest general risk system possible, one containing three parameters: X_1, the log of the parameter governing contamination; X_2, the log of the parameter governing exposure; and X_3, the log of the dose-response parameter. As before, these parameters are assumed to have a joint lognormal

distribution, so that their logs have a joint normal distribution with means M_1, M_2, and M_3 and standard deviations S_1, S_2, and S_3, respectively. For simplicity (and without loss of generality), we shall assume that X_1 and X_2 have covariance rS_1S_2 and that both X_1 and X_2 are uncorrelated with X_3. The log risk Y thus has mean and variance:

$$(6) \qquad EY = M_1 + M_2 + M_3, \quad S_Y^2 = S_1^2 + S_2^2 + 2rS_1S_2 + S_3^2.$$

Two of these parameters (those governing contamination and exposure) are susceptible to control by regulatory action.

Let R_1 denote the social cost of regulating contamination and R_2 denote the social cost of regulating exposure. The former will include such items as the cost of installing emission controls, the value of production and income lost due to shutdowns of plants or banning use of a pesticide on certain crops, the cost of monitoring and enforcing compliance, and the like. The latter will consist of items such as the value of disutility and diminished productivity due to workers' use of protective equipment and the cost of improved ventilation in workplaces. Assume that the two areas of expenditure are separable, that is, that social expenditure on contamination (R_1) affects only contamination (X_1) and the expenditure on exposure (R_2) affects only exposure (X_2). In this case, the means and standard deviations of X_1 and X_2 are functions of R_1 and R_2, respectively, i.e., $M_i = M_i(R_i)$ and $S_i = S_i(R_i)$. The dose-response parameter X_3 is assumed to be unaffected by regulatory expenditure and hence represents a source of uncontrollable risk.

Assuming that both regulatory areas are funded ($R_1, R_2 > 0$) and that the constraint is binding, comparative static analysis shows that these optimal funding allocations display the following four features (see the Appendix).

1. *Total regulatory expenditure and expenditure on each regulatory area will decrease (increase) as the level of maximum allowable risk increases (decreases).* This result is intuitively obvious, since a higher maximum allowable risk level means that the risk is judged to pose less of a threat and thus requires less intervention to meet the agency's safety standard. It is also familiar from the literature on pollution control: the less stringent the pollution standards set, the lower the charges required to meet them and the lower the social cost imposed.

2. *Expenditure on the area with the relative advantage in reducing uncertainty (as well as total expenditure) will increase as the margin of safety increases; however, expenditure on the area*

that has the relative advantage in reducing mean risk may decline. As the agency's aversion to uncertainty rises, it will demand a higher margin of safety, that is, place a larger weight on uncertainty—and hence on marginal reductions in uncertainty—in its decision process. It is thus natural that a greater emphasis on controllable uncertainty will tend to bias regulation in favor of the area in which expenditure produces a greater relative reduction in uncertainty. In keeping with standard theory, one can view this extra cost as a premium paid for reduced uncertainty. What is noteworthy is that in some instances an increased margin of safety may lead to reductions in funding on the area that has the relative advantage in reducing mean risk and hence to poorer performance in controlling risk on the average. This will occur when policies are highly specialized.

3. *Total expenditure and expenditure on the area with the relative advantage in reducing mean risk increase as uncontrollable uncertainty increases; in contrast, expenditure on the area with a relative advantage in reducing uncertainty may decline as uncontrollable uncertainty increases.* The logic of this is eminently practical: the less uncertainty is susceptible to control, the greater will be the emphasis on mean risk reduction and thus the greater the funding allocated to the area with the relative advantage in reducing mean risk. More succinctly, the less one knows about the risks posed by a contaminant, the more careful one should be on the average. This shift of emphasis will only cause a decrease in expenditure on the area with a relative advantage in reducing uncertainty in the case of extreme specialization. In every case, though, the total cost of regulation grows as uncontrollable uncertainty rises.

4. *Total expenditure and expenditure on each area increase (decrease) as the level of uncontrollable mean risk increases (decreases).* Simply put, this result says that a more potent toxin should be regulated more stringently than a less potent one. According to the risk assessment literature [Lowrance, 1976; Starr, 1969; Wilson and Crouch, 1982], people tend to demand more stringent regulation of (or take greater individual precautions in dealing with) risks that are less controllable. This behavior is attributed to risk perception, namely, that people tend to overestimate less controllable risks. The results derived here suggest that this demand for greater stringency may arise not from misperception but from the decision criteria used.

Recall that information-gathering activities can be character-

ized as policies with significant uncertainty effects and negligible mean effects. Equation (5), then, provides a mechanism for determining the efficient allocation of resources for information acquisition as well as for modes of intervention. Propositions 1–4 suggest that the emphasis placed on information acquisition will increase as aversion to uncertainty increases, as uncontrollable mean risk increases and as uncontrollable uncertainty decreases.

Also important to regulators is the problem of allocating resources to different kinds of information-gathering efforts, for example, environmental data collection versus methodological work on dose-response estimation procedures. If information-gathering activities are separable (affect only one parameter) and unbiased (have no mean effects), equation (5) implies that

$$\frac{R_i}{R_j} = \left(\frac{t_i}{t_j}\right)\left(\frac{e_i}{e_j}\right), \tag{7}$$

where relative investment in different types of information-producing activities (R_i/R_j) depends on the relative contributions of different parameters to total uncertainty (t_i/t_j) and on their relative tractabilities with respect to investigation (e_i/e_j). Regulators—and the general public—appear to respond primarily to relative contributions to uncertainty in setting information-gathering priorities. This suggests that there may be significant underinvestment in information-gathering activities whose relative contributions to uncertainty are small but which are extremely tractable.

V. The Value of Risk Reduction

The safety rule approach introduced here takes two key parameters—maximum allowable risk and margin of safety—as given. Choosing a margin of safety P is essentially equivalent to setting a confidence level for hypothesis testing and should thus tend to be noncontroversial. As a practical matter, one can simply choose from the levels prevalent in general scientific work (e.g., 0.95, 0.99). The determination of maximum allowable risk is less straightforward. This parameter is likely to be the subject of political debate and setting a specific risk standard tends to be a political decision. However, the approach introduced here provides an important tool for use in this decision-making process, namely the value of risk reduction.

When the optimality conditions (5) and (3) are binding, every

maximum allowable risk standard Y_0 implies a specific shadow price g, which can be interpreted as society's willingness to pay for marginal reductions in risk with a margin of safety P and which can be used to compare proposed standards with existing regulations. In other words, this value of risk reduction can be used to evaluate the consistency of proposed regulations with established policies or, more broadly, to evaluate the internal consistency of a given set of regulations.

Assuming that the overall risk is concave in expenditure, it is not hard to show that the value of risk reduction displays the following properties:

1. *The value of risk reduction increases (decreases) as the maximum allowable risk decreases (increases); i.e.,* $\partial g/\partial Y_0 < 0$. The stricter the regulatory standard (i.e., the lower Y_0) is, the higher will be the marginal cost of meeting that standard. If a more stringent standard reflects a greater level of safety, then this result can be interpreted as saying that the marginal cost of safety is increasing.

2. *The value of risk reduction decreases (increases) as the margin of safety increases (decreases); i.e.* $\partial g/\partial P < 0$. The higher the margin of safety (or the lower the frequency of violations) demanded, the lower will be marginal cost of meeting any given standard and hence the lower will be the implicit value of risk reduction. Because a higher margin of safety can be interpreted as reflecting greater aversion to uncertainty, this result can also be taken to imply that the implicit value of risk reduction is decreasing in aversion to uncertainty.

3. *The value of risk reduction decreases (increases) as uncontrollable mean risk and uncontrollable uncertainty about risk increase (decrease); i.e.,* $\partial g/\partial M_3 < 0$ and $\partial g/\partial S_3 < 0$. As uncontrollable mean risk rises, the risk-generating process becomes inherently more risky. Thus, the more inherently risky a substance is, the lower will be the value of risk reduction. In addition, the value of risk reduction will be lower for risks that are less well understood; that is, for risks whose inherent (uncontrollable) uncertainty is larger.

4. *The value of risk reduction increases (decreases) as the marginal productivity of expenditure in reducing mean risk or uncertainty about risk increases (decreases); i.e.* $\partial g/\partial M_i' > 0$ *and* $\partial g/\partial S_i' > 0, i = 1, 2$. As regulatory measures become more effective in reducing mean risk or uncertainty about risk, the value of risk reduction grows.

VI. Conclusions

Uncertainty is a principal characteristic of current environmental health problems and a major stumbling block to efforts to fashion appropriate policies for dealing with them. This paper introduces a methodology for coping with this uncertainty and analyzes the characteristics of the optimal mix of policies for achieving any present maximum allowable risk standard with a given margin of safety. Moreover, the uncertainty-adjusted value of risk reduction developed here can be used in benefit-cost analysis.

The analysis here applies to the micro-level problem of determining policies for dealing with specific environmental health risks. A natural extension is the more general problem of determining the social cost of risk reduction and the maximum allowable risk level simultaneously. This would require combining uncertainty-adjusted tradeoffs between social cost and risk with an indifference map representing social preferences regarding risk and social cost to yield an optimal cost-risk combination and implicit value of risk reduction with a given margin of safety. Such a generalized approach could then be used to evaluate health and safety policy on a national or international level where risks from different sources are compared with income, production and growth.

Appendix

The regulatory decision problem is

$$\max_{R_1, R_2} -R_1 - R_2$$

subject to

$$M_1(R_1) + M_2(R_2) + M_3 + F(P)\,[S_1^2(R_1) + S_2^2(R_2) + 2rS_1(R_1)S_2(R_2) + S_3^2]^{1/2} - Y_0 \leq 0.$$

Assume that $R_1, R_2 > 0$ and that the constraint is binding. Denote the appropriate derivatives with primes. The necessary conditions for an optimum are

$$-h - [M_1' + (F(P)/S_Y)(S_1 + rS_2)S_1'] = 0$$
$$-h - [M_2' + (F(P)/S_Y)(S_2 + rS_1)S_2'] = 0$$
$$M_1 + M_2 + M_3 + F(P)S_Y - Y_0 = 0,$$

where $h = 1/g$.

Let $H_{ii} = M_i'' + F(P)\,S_Y(t_iS_i)S_i'' + [F(P)/S_Y](S_i)^2[1 -$

$t_i S_Y/S_i)2] > 0$ because $M_i'' > 0$ and $S_i'' > 0$ and $H_{12} = [f(P)/S_Y]S_1'S_2'[-(1-r)S_1S_2/S_Y^2] \leq 0$, since $S_1', S_2' < 0$ and $0 \leq r \leq 1$. The determinant of Hessian is $|H| = h(H_{11} + H_{22} - 2H_{12}) \geq 0$, so that the necessary conditions are also sufficient.

Total differentiation of the necessary conditions yields

$$\begin{pmatrix} -H_{11} & -H_{12} & -1 \\ -H_{12} & -H_{22} & -1 \\ -h & -h & 0 \end{pmatrix} \begin{pmatrix} dR_1 \\ dR_2 \\ dh \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} dY_0 + \begin{pmatrix} F'(P)S_Y(t_1e_1/R_1) \\ F'(P)S_Y(t_2e_2/R_2) \\ -F'(P)S_Y \end{pmatrix} dP$$

$$+ \begin{pmatrix} 0 \\ 0 \\ -1 \end{pmatrix} dM_3 + \begin{pmatrix} -F(P)S_Y(t_1e_1/R_1)(t_3/S_3) \\ -F(P)S_Y(t_2e_2/R_2)(t_3/S_3) \\ -F(P)S_Y(t_3/S_3) \end{pmatrix} dS_3,$$

which implies that

PROPOSITION 1. $\partial R_i/\partial Y_0 = (-1/|H|)(H_{jj} - H_{12}) < 0$. Also $\partial R_1/\partial Y_0 + \partial R_2/\partial Y_0 = -1/h = -g < 0$.

PROPOSITION 2. $\partial R_i/\partial P = [F'(P)S_Y/|H|](H_{jj} - H_{12}) - h[(t_ie_i/R_i) - (t_je_j/R_j)] \geq 0$ if $|t_ie_i/R_i| \geq |t_je_j/R_j|$. Otherwise, sign $[\partial R_i/\partial P]$ = sign $[M_i' - M_j' - F(P)S_Y(H_{jj} - H_{12})/h] < 0$ when the mean effect of policy i is large relative to that of policy j. Also, $\partial R_1/\partial P + \partial R_2/\partial P = F(P)S_Y/h > 0$.

PROPOSITION 3. $\partial R_i/\partial S_3 = (t_3/S_3)/|H| - h(M_i' - M_j') + (H_{jj} - H_{12}) \geq 0$, if $M_i' > M_j'$. Otherwise, sign $[\partial R_i/\partial S_3]$ = sign $[(t_ie_i/R_i) - (t_je_j/R_j) - (H_{jj} - H_{12})/h] < 0$ when the uncertainty effect of policy i is large relative to that of policy j. Also, $\partial R_1/\partial S_3 + \partial R_2/\partial S_3 = F(P)S_Yt_3/hS_3 > 0$.

PROPOSITION 4. $\partial R_i/\partial M_3 = -\partial R_i/\partial Y_0$.

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