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Douglas Krieger
John P. Hoehn

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Department of Agricultural Economics
MICHIGAN STATE UNIVERSITY
East Lansing, Michigan

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Reports of food contamination incidents and environmental hazards raise questions about the safety of our environment and food supply. Examples of such risks include radon gas in homes, pesticide residues on fruits and vegetables, EDB contamination of grain products, and chemical residues in fish. When people learn of contamination they may incur costs to avert risk. Costs may be monetary, as in the purchase of a water filter, or non monetary, as when a valued activity is given up to limit exposure. In either case individuals suffer a welfare loss.

Several studies estimate welfare losses associated with food contamination incidents. Shulstad and Stoevener (1978) found that pheasant hunters in Oregon reduced hunting activity and suffered a welfare loss when informed of mercury contamination. Swartz and Strand (1981) estimated welfare losses associated with information about contamination in oysters. Foster and Just (1989) found that residents of Hawaii reduced milk consumption and suffered a welfare loss when they learned of heptachlor contamination.

Two fundamental conclusions of decision theory are that the ex ante and ex post values of costless information are nonnegative (Chavas and Pope, 1984; Hirshleifer and Riley, 1979). Positive ex ante information value implies that people are willing to pay a positive amount to learn if they are exposed to health risks or not. At first glance this seems inconsistent with measured ex post welfare losses. Together these conclusions seem to imply that people are willing to pay some positive amount for information that may ultimately make them worse off. Positive ex post information value seems even more contradictory. This implies that people are willing to pay for information even when they know welfare will be reduced.

One source of this seeming contradiction may lie in a confusion about the source of welfare losses and information value. The empirical studies cited above correctly determine that *contamination* causes an ex post welfare loss. However, it is easy to conclude from some studies that *information* causes the loss. That the loss is *related* to information is trivial, if people are not aware of the problem behavior is unchanged and no loss occurs. In this paper we show that contamination can cause a loss of welfare that is consistent with nonnegative ex ante and ex post information values.

A second objective of this paper is to explore how assumptions about the reliability of risk assessments affect estimates of information value. Bayesian analysis recognizes that perceptions of risk are influenced by people's subjective perceptions of the reliability of information. However, some studies refer to "correct" perceptions of risk by which they often mean technical risk assessments generated by experts. The use of technical risk assessments in this manner implies that expert's judgments of risk are completely reliable. Johnson (1988) examined the value of information about EDB contamination of grain products and argued that information can have negative value if correct risk perceptions can be identified.

The first section of this paper addresses the plausibility of "correct" risk perceptions in the context of health risk assessments. We conclude that technical risk assessments are necessarily subjective and are not the appropriate basis for evaluating the welfare impacts of health risk information. The next section focuses on the distinction between ex post welfare effects and ex ante information value. We show that failure to differentiate these concepts may lead to confusion about the value of information and appropriate regulatory policies.

A final section adapts Bayesian measures of welfare loss and information value to a simple supply and demand analysis. The approach extends the current literature by considering changes in both producers and consumers surplus. The inclusion of supply considerations highlights the distribution of gains and losses between producers and consumers and suggests some implications for information policy. The graphical presentation also links the Bayesian framework to more familiar supply and demand analysis in an easily understood manner.

RISK PERCEPTION IN A BAYESIAN FRAMEWORK

Bayesian analysis explicitly models individual perceptions of risk as a function of prior perceptions, new information, and the perceived reliability of information. Individuals may form different risk perceptions if they have different prior perceptions, they receive different information, or they have different beliefs about the reliability of information. Risk assessments are subjective in this framework because they rely on people's subjective beliefs about information. Perceptions of information reliability may depend on beliefs about test procedures generating the information, faith in the integrity of the information source, or past experience with the agency providing the information. Studies that measure information value relative to "correct" technical risk assessments implicitly assume that experts and lay people agree about risks.

Two studies explicitly estimated information effects relative to technical assessments of risk. Swartz and Strand (1981) found that imperfect information led consumers to incur avoidance costs that were not warranted by expert's assessments of risks. Johnson (1988) showed that the sign of information value depends on the information, and associated action, that is assumed correct. He concludes that information that results in behavioral adjustments towards correct action has positive value while information that increases the discrepancy between correct and actual behavior has negative value.

Are Technical Health Risk Assessments "Correct"?

Judgments regarding the reliability of technical risk assessments can substantially alter policy prescriptions. Johnson's conclusion implies that people may be better off if some information is withheld. However, researchers who believe that information is properly evaluated relative to individual perceptions of risk conclude that information value must be nonnegative. This result implies a policy of full disclosure of risk information. In this section we examine whether the use of technical risk assessments is warranted in the context of health risk assessment.

Fischhoff (1989) claims that experts, as well as lay people, must rely on judgment in assessing risk. He discusses five aspects of scientific risk assessment that require judgment. First, risk assessment requires a model of the process creating the hazard. Judgment enters model development in the choice of which elements of the process to consider. Judgments involved in developing a model of food contamination risk might include choices about which segments of the population are likely affected, which health effects are possible, or which channels of exposure to consider.

Second, choices must be made that impose conceptual order on the model. A model that investigates all possible interactions among elements would be analytically intractable and the results would be difficult to interpret. For a model of food contamination risks these judgments might include the choice of which factors other than exposure to contamination might be useful in explaining observed health effects.

Third, risk assessors must judge the value of model parameters. Some parameters can be fairly accurately estimated (*e.g.*, the number of people comprising some subset of the population). However, less statistical evidence may exist for other parameters (*e.g.*, the number of cancer cases in the affected population). The quality of the analysis depends on the accuracy of parameter estimates. Evidence suggests that scientists do not always apply statistical concepts appropriately. Even among researchers with some statistical expertise, selected sample sizes are often too small to provide adequate tests of hypotheses.

Fourth, when an assessment is complete scientists need to appraise the quality of their analysis. They need to judge whether the analysis is good enough for its intended purpose. For example, an epidemiologic study should link specific health effects to exposure with some degree of confidence. The choice of appropriate methods of analysis and the desired confidence in results both represent necessary judgments by the researcher.

Finally, scientists use judgment in the way they elicit responses to research questions. People think about risks in different ways and in some cases may have no preconceived beliefs or values. Because of these differences it may be difficult to compare responses from different individuals. It may also be difficult for the researcher to avoid influencing responses, especially in the situation where respondent's beliefs and values are not well formed.

Further, Fischhoff contends that scientists, like lay people, may be overconfident about the state of their knowledge. He shows how estimates of several physical phenomena such as the speed of light and Planck's constant have changed over time. New estimates often fall outside the confidence intervals placed on previous estimates. Figures 1 and 2 reproduce Fischhoff's graphical illustration of the change in these estimates over time.

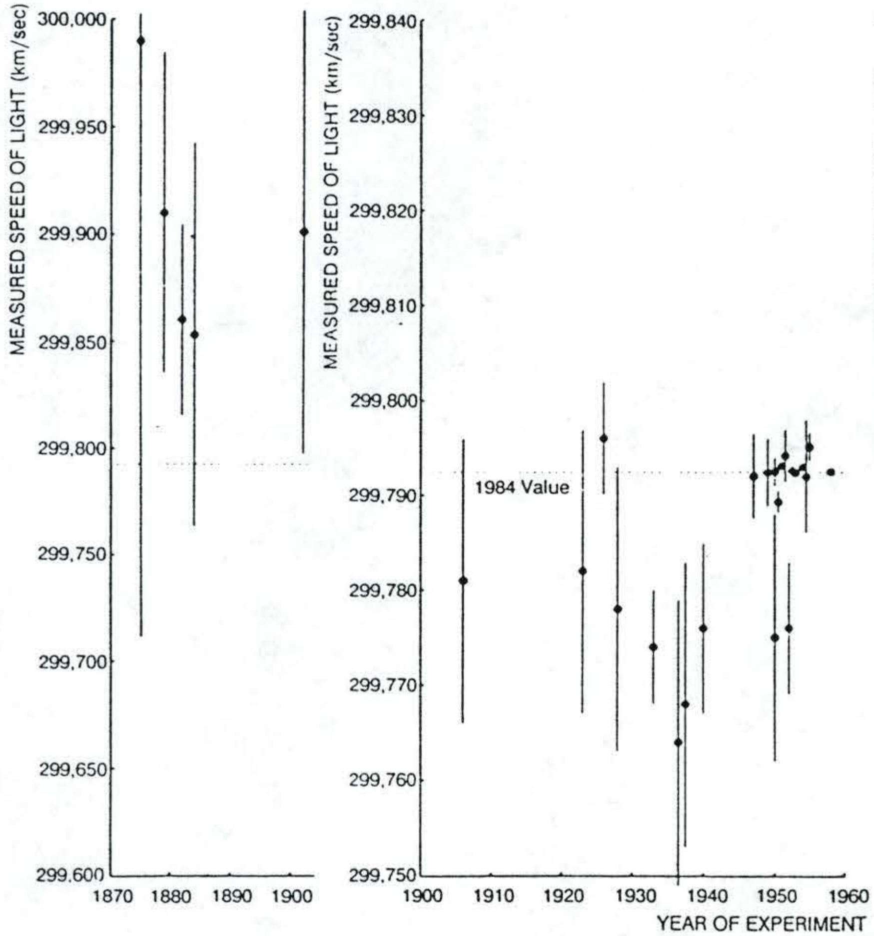
Fischhoff's work implies that technical risk assessments are unavoidably influenced by researcher's values. Scientists may have different values than lay people. Studies that employ technical risk assessments to generate policy prescriptions effectively impose the values of scientists on the affected population. When technical risk assessments differ from those of lay people the public will prefer policies consistent with their perception of risk.

A great deal of uncertainty exists about the health risks associated with food and environmental contamination. Greater uncertainty implies the need for more judgment when assessing risks. Thus, even experts would be expected to disagree about the health risks associated with a contamination incident. With no "correct" perception of risk the value of information is properly measured relative to people's subjective posterior beliefs. The uncertain and subjective nature of food and environmental risks suggests a Bayesian analysis of the value of information.

WELFARE EFFECTS AND INFORMATION VALUE IN A BAYESIAN FRAMEWORK

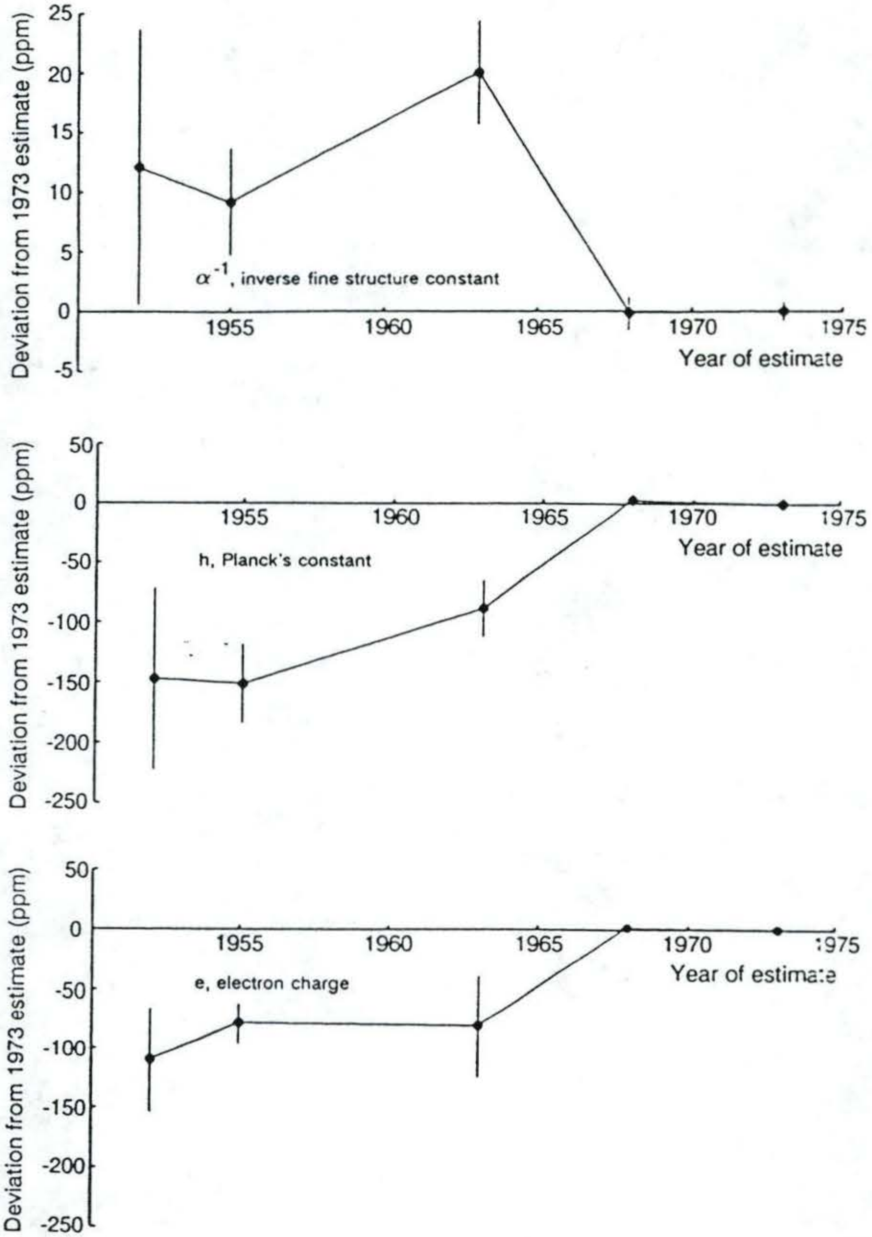
Information consists of a set of signals. For instance, information about food contamination might contain two possible signals, a signal of contamination and a signal of safety. Prior to receipt of information the particular signal that is forthcoming is unknown. Information value measured at this stage is *ex ante* with respect to information and must be based on the perceived probability of each possible signal. Receipt of information resolves the uncertainty about which signal will be received.

Figure 1 - Changes in Physical Constants Over Time



Calibration of confidence in estimates of physical constants. SOURCE: Henrion and Fischhoff, 1986. Copyright © 1986 by the American Association of Physics Teachers.

Figure 2 - Changes in Physical Constants Over Time



Recommended values for fundamental constants, 1952 through 1973. SOURCE: Henrion and Fischhoff, 1986.

The measured value of a received signal is *ex post* with respect to information. Ex post values are useful in evaluating the effects of a particular signal. However, in the context of designing policy information must be evaluated ex ante, before the specific signal to be received is known. This section uses a Bayesian approach to distinguish between measures of ex ante information value, ex post signal value, and ex post welfare change.

Valuation of Alternative Acts

Bayesian analysis defines measures of information value and welfare loss by comparing the value of alternative acts given different perceptions of state probabilities. Three values are central to Bayesian analysis of information, the prior expected utility of the prior optimal act, the posterior expected utility of the prior optimal act, and the posterior expected utility of the posterior optimal act.

Consider an individual faced with choosing from a set of actions, $A=\{a_1,a_2,\ldots,a_J\}$. Utility depends on the chosen action and on the realization of a probabilistic event (state) that is beyond the individual's control. Denote the set of all possible states as $S=\{s_1,s_2,\ldots,s_K\}$. While the state that ultimately occurs is unknown, the individual has some subjective prior perception of the probability of occurrence of each state, $P(s_k)$. The individual's decision problem is to choose an action to maximize the expectation of utility over state probabilities. Define the action that solves this problem as a^*. The *prior expected utility of the prior optimal act* is then

(1) $$E[u(a^*,S)] = \max_a \Sigma_k P(s_k)\, u(a,s_k) = PrPr.$$

Now suppose that the individual has the opportunity to obtain information about the distribution of state probabilities. Information consists of a set of unique signals, $Y=\{y_1,y_2,\ldots y_I\}$. A signal that contains useful information causes the individual to revise prior perceptions of state probabilities. Bayes's theorem defines posterior probabilities as a function of prior and likelihood probabilities

(Anderson, Dillon and Hardaker, 1977). Likelihood probabilities reflect people's perception of the information provided by the test and may incorporate their perceptions of the accuracy of the test or their faith in the agency providing the test.

Suppose an individual receives signal y_i. They combine perceptions of the signal with prior beliefs to form posterior perceptions of state probabilities, $P(s_k | y_i)$. The posterior state probabilities are conditional on the signal received. Evaluated with posterior probabilities the expected utility of the prior optimal act may differ from its prior expected utility. The *posterior expected value of the prior optimal act* given receipt of signal y_i is

$$(2) \qquad E_{yi}[u(a^*,S)] = \Sigma_k P(s_k | y_i)\, u(a^*,s_k) = PoPr$$

where the subscript on the expectations operator denotes an expectation with respect to posterior probabilities conditional on signal y_i.

When an individual revises perceptions of state probabilities they may find that the prior optimal act no longer maximizes expected utility. Define the act that maximizes expected utility given signal y_i as a^i. Then the *posterior expected utility of the posterior optimal act* given signal y_i is

$$(3) \qquad E_{yi}[u(a^i,S)] = \max_a \Sigma_k P(s_k | y_i)\, u(a,s_k) = PoPo.$$

By the definition of a maximum action a^i maximizes expected utility given signal y_i. Thus, the posterior expected utility of the prior optimal act (equation 2) can be no greater than the posterior expected utility of the posterior optimal act (equation 3).

Net Welfare Loss Due to Contamination

Clearly, contamination of food or the environment can cause an ex post loss of consumer welfare. When made aware of health risks consumers may incur costs or change behavior to avert risk. These costs represent a loss of welfare relative to the no contamination situation. Shulstad and Stoevener and Foster and Just both estimated consumer surplus losses associated with contaminated food.

These studies define ex post welfare loss as the difference in utility levels before and after awareness of contamination. In terms of the values defined above this is the difference between the prior utility of the prior optimal act and the posterior utility of the posterior optimal act

$$(4) \qquad E[u(a^*,S)] - E_{y_i}[u(a^i,S)] \\ = PrPr - PoPo.$$

Contamination caused a loss of welfare in both cases because people incurred avoidance costs to reduce risk (*e.g.* gave up pheasant hunting or reduced milk consumption).

Foster and Just recognize this loss as only one component of the total welfare effect of a contamination incident. They interpret equation (4) as the welfare loss due to contamination net of the positive ex post value of a signal from the information system. Contamination causes a loss of welfare but information allows people to avert some of the loss.

To clarify the relationship between the net welfare loss due to contamination and the positive ex post value of a signal consider the decomposition of equation (4)

$$(5) \qquad PrPr - PoPo \\ = PrPr - PoPr + PoPr - PoPo \\ = (PrPr - PoPr) - (PoPo - PoPr)$$

The first part of the final expression in equation (5) is the gross welfare loss due to contamination. The second part of the expression is the ex post value of a signal.

Gross Welfare Loss Due to Contamination

Consider an individual who learns of an existing contamination problem to which their actions have exposed them. Once aware of the problem the person may wish to change their behavior to avert some of the risk. However, they may still worry about the consequences of their actions taken in ignorance. The gross welfare loss due to contamination is the loss in utility due to changed perceptions of risk when there is no opportunity to change behavior. In terms of the values defined above it is the difference in the valuation of the prior optimal act as perceptions change

(6) $$E[u(a^*,S)] - E_{yi}[u(a^*,S)] = PrPr - PoPr.$$

This loss is due to changed perceptions of contamination. It differs from the measure of net welfare loss because it does not consider the effects of risk averting changes in behavior.

Ex Post Signal Value

A signal from an information system has value because it provides an opportunity to change behavior. When a person becomes aware of a health risk they suffer a welfare loss associated with worrying about the consequences of past behavior. The receipt of a signal about the risk permits them to recognize past behavior as a mistake and engage in risk averting behavior. The ex post value of the signal is the increase in utility it makes possible over the mistake it helps avoid. Ex post signal value is the difference between the maximum expected utility possible given posterior perceptions of contamination and the expected utility of the mistaken prior action. This is the difference between the posterior expected utility of the posterior optimal act and the posterior expected value of the prior optimal act.

(7) $$E_{yi}[u(a^i,S)] - E_{yi}[u(a^*,S)] = PoPo - PoPr$$

Because the posterior expected utility of the prior optimal act can be no larger than the posterior expected utility of the posterior optimal act the ex post value of a signal must be nonnegative. If a signal does not change behavior then $a^i = a^*$, $E_{yi}[u(a^i,S)] = E_{yi}[u(a^*,S)]$, and the signal has no value.

Ex Ante Information Value

The above analysis illustrates the difference between ex post welfare change and signal values. The conclusion that ex post signal value must be nonnegative holds for ex ante information value as well. Before a specific signal is received the ex ante value of an information system is the expectation of signal values over the probability that the specific signal will be received (Hirshleifer and Riley, 1979).

(8) $$\Sigma_i P(y_i) \{E_{yi}[u(a^i,S)] - E_{yi}[u(a^*,S)]\}$$

where $P(y_i) = \Sigma_k P(s_k) P(y_i|s_k)$ is the probability of receiving signal y_i.

Ex ante information value must be nonnegative because it is the weighted sum of nonnegative ex post signal values. If none of the signals that comprise an information system are expected to change behavior then the ex ante value of information is zero.

BAYESIAN VALUES IN A SUPPLY AND DEMAND MODEL

The decomposition of welfare loss defined in the previous section followed the work of Foster and Just and considered only changes in consumer behavior. In this section we extend their analysis to include changes in both producers and consumers surplus in a simple supply and demand framework.

We find that inclusion of supply considerations affects the magnitude of measured welfare losses and information value. It also yields some insights into the distribution of gains and losses between consumers and producers.

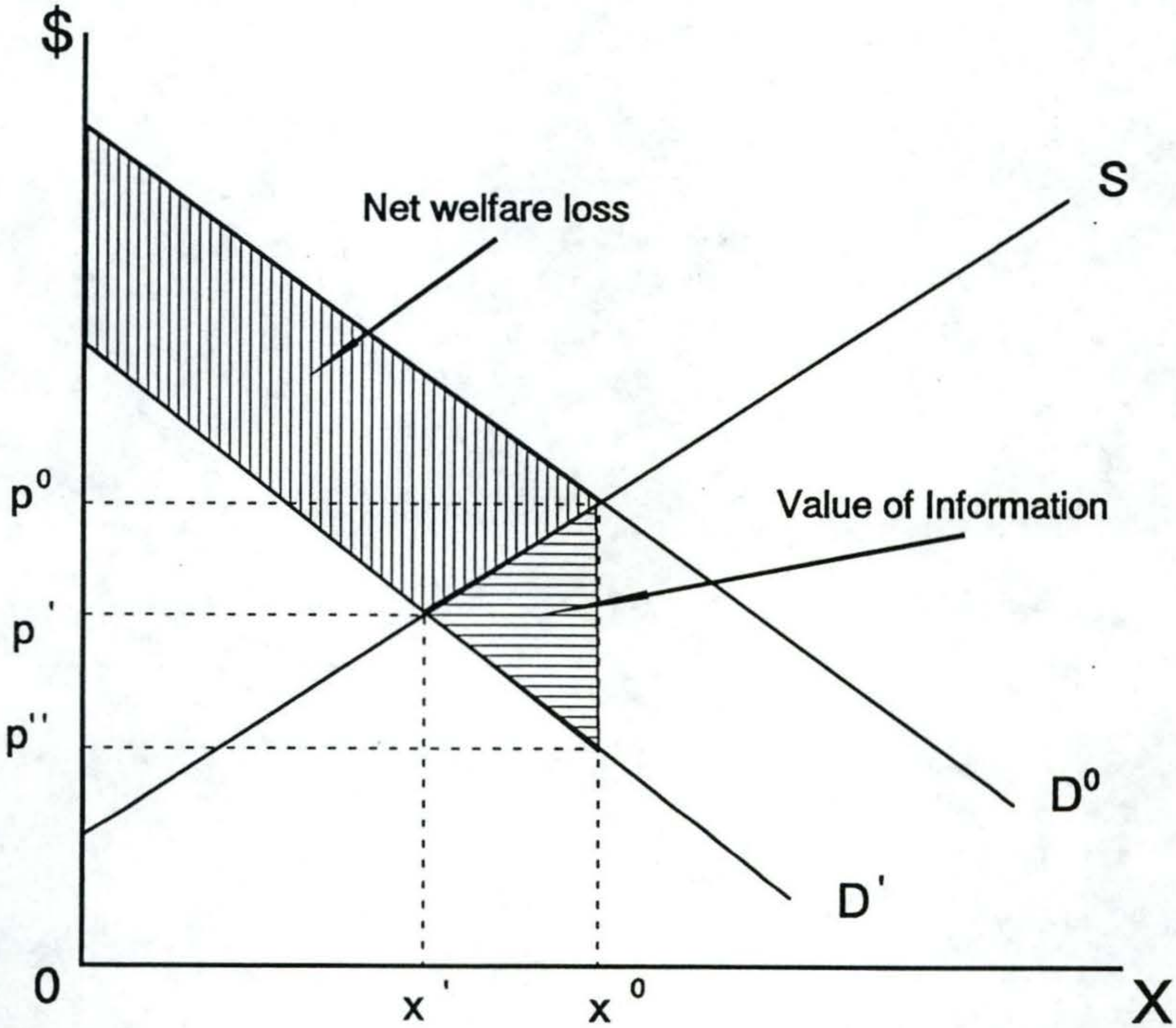
Figure 3 describes a simple supply and demand model for a possibly contaminated good, X. The supply relationship for the good is described by the curve S. With only prior information about the quality of X compensated demand is given by D^0. The intersection of S and D^0 yields the initial equilibrium at price p^0 and quantity x^0. Now suppose that a signal is received that increases the expectation that X is contaminated. The contamination causes the compensated demand curve to shift in to D'. The decline in perceived quality decreases the quantity demanded at any given price. The posterior equilibrium is at price p' and quantity x'. Price p'' is the price at which people would demand the initial quantity of X given their posterior perceptions of quality.

We have defined the net welfare loss due to contamination as the difference between the prior value of the prior act and the posterior value of the posterior act. The prior value of the prior act is the sum of producers and consumers surplus at the initial equilibrium (p^0,x^0). The posterior value of the posterior act is the sum of producers and consumers surplus at the posterior equilibrium (p',x'). The net welfare loss is thus the area shaded by horizontal lines.

The ex post value of a signal that causes demand to shift from D^0 to D' is the difference between the posterior value of the posterior act and the posterior value of the prior act. The posterior value of the prior act is the value to consumers of consuming x^0 at price p'' (the area under D' between 0 and x^0) minus the cost to producers to provide x^0 (the area under S between 0 and x^0). The posterior value of the prior act is thus the sum of the two triangular areas bounded by S, D', x^0, and the vertical axis. The triangle on the right (shaded with vertical lines) represents a negative value. We have already defined the posterior value of the posterior act as the area of the left triangle. Thus, the ex post value of the signal is represented by the area of the vertically shaded triangle, now a positive value.

The area representing information value is similar to the dead weight loss imposed by an *ad valorem* tax. A tax drives a wedge between supply and demand and causes people to consume too little. In the model described above ignorance causes people to consume too much.

Figure 3 - Net Welfare Loss and Information Value



Elasticity of Supply

The relative magnitude of net welfare loss and information value is sensitive to the assumed elasticity of supply. As supply becomes relatively inelastic a given shift in demand brings about a smaller change in equilibrium quantity demanded than in equilibrium price. Consumers benefit from the reduction in price and suffer a relatively small loss of consumer surplus associated with reduced consumption. Producers suffer a relatively large surplus loss that is largely transferred to consumers in the form of lower prices. The net welfare loss becomes larger as supply becomes more inelastic while the value of information declines. In the extreme case of perfectly inelastic supply the value of information is zero and net welfare loss is maximized.

When supply is relatively elastic a given shift in demand prompts a large change in equilibrium quantity demanded relative to the change in equilibrium price. The relatively large behavioral response implies a greater value of information and a subsequent decrease in net welfare loss. The loss of producers surplus is small relative to consumers surplus losses. At the extreme of perfectly elastic supply information value is maximized and net welfare loss minimized.

To illustrate the sensitivity of information value estimates to supply elasticity we recalculated Foster and Just's values for milk contamination information under two alternative elasticity assumptions. Their estimate of information value with an implicit assumption of perfectly elastic supply was \$9.33 per person. With an elasticity of supply of .5 we calculated information value to be \$6.01 per person, 64 percent of Foster and Just's estimate. The short run supply elasticity of milk is probably close to .2. Using this elasticity estimate we calculated the value of information to be \$5.15 per capita, 54 percent of Foster and Just's estimate.

The distribution of gains and losses as supply elasticity changes provides some insights into information policies. When information about a contamination incident is first released producers would be expected to incur surplus losses if short run supply is relatively inelastic. At the same time consumers would gain from lower prices and information would have little value because behavior would change very little. In the long run, as supply becomes more elastic, producer losses would decline as they adjusted to the shift in product demand. Less inelastic long run supply would lead to an increase in prices and the short run transfer of benefits from producers to consumers would decrease. Price increases would prompt consumers to change behavior which would bring about an increase in the value of information.

SUMMARY

Careful attention to the definition and application of values associated with information can prevent interpretations of research results that imply counter intuitive policy prescriptions. Contamination may cause welfare loss as people suffer health problems or worry about the consequences of prior, uninformed, actions. Ignorance of contamination may cause a dead weight loss as people bear more risk than they would choose if informed. Information prevents this loss because it provides people the opportunity to choose actions that are more consistent with the level of risk they wish to bear. The value of information must be nonnegative because it makes possible action that is more consistent with preferences. Because information can not make people worse off it will never be in the public interest to withhold costless information.

When the analysis includes supply considerations estimates of welfare loss and information value are sensitive to assumptions about the elasticity of supply. In the short run much of the loss associated with contamination falls on the producer while consumers may benefit from lower prices. In the long run, however, with more elastic supply producer loss is reduced and information value increases.

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