ISSN 1835-9728

Environmental Economics Research Hub
Research Reports

The value of information in biosecurity risk-benefit assessment: an application to red imported fire ants

Michael Ward and Tom Kompas

Research Report No. 50

March 2010

About the authors

Dr. Michael Ward is an associate professor at the Crawford School of Economics and Government at the Australian National University.

Professor Tom Kompas is the director of the Crawford School of Economics and Government at the Australian National University.

Environmental Economics Research Hub Research Reports are published by The Crawford School of Economics and Government, Australian National University, Canberra 0200 Australia.

These Reports present work in progress being undertaken by project teams within the Environmental Economics Research Hub (EERH). The EERH is funded by the Department of Environment and Water Heritage and the Arts under the Commonwealth Environment Research Facility.

Crawford School of Economics and Government

THE AUSTRALIAN NATIONAL UNIVERSITY

http://www.crawford.anu.edu.au

Draft version — 2010.02.15

Policy makers are confronted with uncertainty on a daily basis, especially in complex areas like biosecurity. One option is to make decisions based on the information at hand, ideally using an expected value or expected utility framework. Another option is to call for further study to reduce or eliminate some uncertainties before making a decision. It is no surprise that such information has positive expected value, so long as it allows improved decisions to be made with positive probability. Since information has a cost, as well as a value, a fundamental question facing policy makers is whether that value exceeds the cost.

This paper makes three practical contributions to addressing that question for binary choices, such as whether to implement or to forego a particular policy. First, it analyses the determinants of the value of information, and how that value changes with features of the problem. Second, it uses this analysis to derive simple rules of thumb which provide upper bounds on the value of additional information. Third, it provides a practical application of the value of information in deciding whether to attempt eradication of the red imported fire ant.

Of course, information for decision making has long been recognized as an economic good, an idea Marschak (1954) was one of the first to develop. Moreover, the concept has played an important role in the development of environmental economics. Information can be deliberately gathered, or it can emerge over time. In the latter case, Arrow and Fisher (1974) show that there is a so-called quasi-option value to delaying an irreversible decision until that information is revealed. As Conrad (1980) shows, quasi-option value is in its simplest form equivalent to the ordinary value of information for decision making. The vast literature on methods to provide information for environmental decision making is clear evidence of the value of information. However, relatively little analysis of the value of precision in this information has been done. For example, should a decision maker rely on a rough environmental value transfer, or commission an original choice modelling study narrowly targeted to the exact decision at hand?

1. Model

We adopt the standard framework used by most treatments of the economic value of information, such as that of Raiffa and Schlaifer (1961), where the decision maker maximizes the expected value of some objective function conditional on a given information set. In our case, the decision maker seeks to maximize expected net benefit when faced with the dichotomous choice of whether to implement some policy. For the moment, we assume that benefits B of the policy are uncertain, and costs C are known. The decision maker has an initial information set which helps inform beliefs about the plausibility of possible values for B, which we will represent by a prior probability density function $f(B)$. We assume that the decision maker maximizes expected net benefits, and so only implements the policy if $\mathbf{E}_B\, B > C$. So, the expected payoff of a potential policy, given the optimal decision, is $\max(\mathbf{E}_B\, B - C, 0)$.

The decision maker can gather additional information to reduce uncertainty about the true value of B. Conditional on the new information set I, the payoff of the optimal conditional decision is $\max(\mathbf{E}_{B|I}\, B - C, 0)$. Before the information is acquired its value is, of course, unknown. So the *ex ante* expected payoff, $\mathbf{E}_I \max(\mathbf{E}_{B|I}\, B - C, 0)$, is the relevant factor. The expected value of such information is the improvement in expected payoff:

$$\mathbf{E}_I \max(\mathbf{E}_{B|I}\, B - C, 0) - \max(\mathbf{E}_B\, B - C, 0). \tag{1}$$

Lawrence (1987) discusses alternative ways to compute this measure.

In this analysis, we are particularly interested in the value of complete information because it provides an upper bound on the value of partial information. If the cost of a proposed study exceeds the value of complete information, that is sufficient grounds to discard the option of funding the study. It will generally be simpler and more transparent to calculate this upper bound than to simulate over the various partial information sets that a study might produce. The expected payoff from full information (VOI), which exactly identifies B, is

$$(2) \qquad VOI = \mathbf{E}_B \max(B - C, 0) - \max(\mathbf{E}_B\, B - C, 0).$$

If multiple sources of uncertainty are independent, then only a slight reinterpretation of formula (2) is required to handle the value of learning about a subset of those sources. For example, suppose that C is also uncertain, so that the decision maker must choose based on expected costs rather than actual costs. If B and C are distributed independently, discovering B does not provide information about C. In that case, the VOI for B alone is still (2) so long as we interpret C in the expression as *expected* costs. More generally, suppose that there are multiple components of the total benefits B. In the case of RIFA, avoiding trade restrictions and avoiding ant stings are both parts of eradication benefits, but very different types of studies would be required to pin down the exact values. Again, if we want to know the VOI from an ant-sting study alone, formula (2) still applies if we view B as the ant-sting component and we view C as expected costs *net* of all other expected benefits. The key element to this interpretation is that B should capture all elements we learn about from a given study and C should capture all those elements we will not learn about.

To gain some intuition, it is helpful to write out the VOI in terms of the prior distribution $f(B)$, where the upper and lower support of B are $\overline{B}$ and $\underline{B}$ respectively. If the prior optimal decision is to forego the policy, then

$$(3) \qquad VOI = \mathbf{E}_B \max(B - C, 0) = \int_C^{\overline{B}} (B - C) f(B) dB.$$

Note that VOI depends only on the density f where $B > C$, which is the range where the decision would be regretted. Multiplying and dividing the above formula by the probability mass in this regrettable region, we get

$$(4) \qquad VOI = \int_C^{\overline{B}} f(B) dB \times \int_C^{\overline{B}} (B - C) \frac{f(B)}{\int_C^{\overline{B}} f(b) db} dB.$$

This expression has a simple interpretation. It is the the probability of making a regrettable decision, times the expected loss conditional on having made a a regrettable decision. Similarly if the the prior optimal decision is to implement the policy then

$$(5) \qquad VOI = \mathbf{E}_B \max(B - C, 0) - (\mathbf{E}_B\, B - C) = \int_{\underline{B}}^{C} (C - B) f(B) dB.$$

In this case, VOI can again be interpreted as the the probability of making a regrettable decision, times the expected loss conditional on realizing a net loss from the decision:

$$(6) \qquad VOI = \int_{\underline{B}}^{C} f(B) dB \times \int_{\underline{B}}^{C} (C - B) \frac{f(B)}{\int_{\underline{B}}^{C} f(b) db} dB.$$

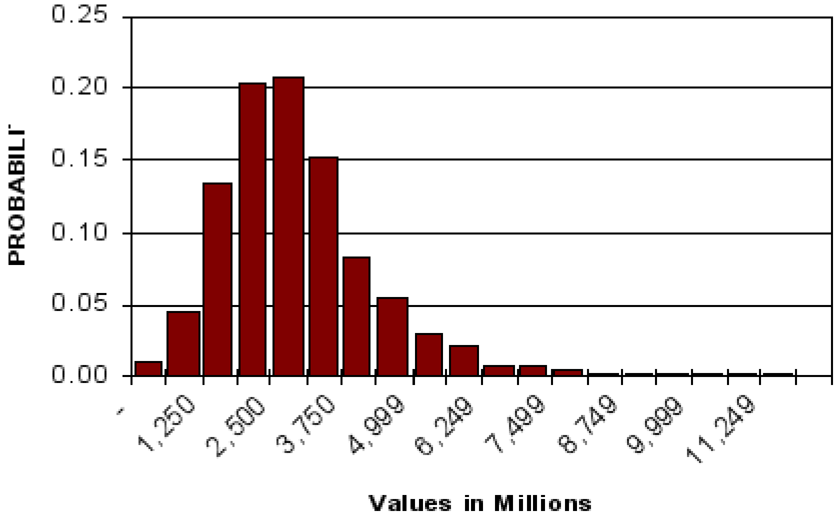
2. Application to RIFA

According to McCubbin and Weiner (2002) fire ants are thought to have entered Australia via shipping containers. There are two RIFA epicentres, one on the east of Brisbane around the port area, the other in Brisbane's western suburbs and part of Ipswich. They are pests, not only because of the physical pain their sting can inflict, but because their mound-building activity can damage plant roots, lead to loss of crops, and interfere with mechanical cultivation. It is not uncommon for several fire ant mounds to appear suddenly in a suburban yard or a farmer's field, seemingly overnight. Ecological modelling shows that the ants are capable of surviving in most parts of Australia, while spread modelling suggests that, if uncontrolled, the ants could spread up to 2 million square kilometres (ie, about a quarter of the area of Australia) over the next few decades. To date, almost AU $250 millon have been allocated for controlling the Southeast Queensland infestation (Australian Government 2007).

Kompas and Che (2001) estimated the benefits of control or eradication of RIFA in Australia. These expected benefits are simply the savings in damage costs from RIFA in lieu of preventive measures. The net present value of these expected benefits over a 30 year horizon was about AU$2.8 billion, well above the control costs to date. Of this, over 50% was loss in residential property value from infestation, and another 24% was residential treatment costs. A variety of other impacts, such as damages to cattle, golf courses, and electrical equipment accounted for the remainder.

Since RIFA was still in the initial stages of spread in Australia there was little direct Australian data available to estimate potential damages likely to result from this pest. Kompas and Che formed their estimates for most categories of potential damage in Australia by examining impacts from infestations in the United States. Such value transfers inherently have a high degree of uncertainty, especially in an inter-continental context (Lindhjem and Navrud 2008). For the single largest category of damage, loss in residential property value, no United States data was

FIGURE 1. Probability distribution of damages from RIFA.

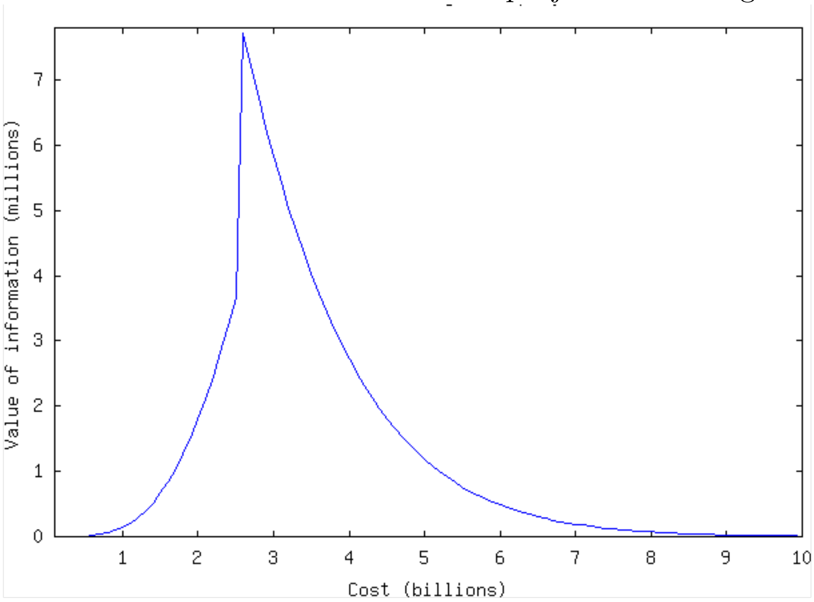


available, so Kompas and Che assigned a central guess of 0.1% of property value, with a risk assessment drawn from a normal distribution.

Since all cost measures as well as other parameters such as the discount rate and spread rate were uncertain, Kompas and Che performed a risk assessment of the potential damages of RIFA based on a calculated variance and chosen probability distribution for the value of each parameter. The technique allows for a simulated stochastic process with parameter values for each realisation drawn from a Monte Carlo process without replacement. Tabulating the frequency of outcomes in the simulation, displayed in Figure 1, provides a reasonable estimate of the prior probability density function over benefits, $f(B)$.

Examining the probability distribution of benefits, a trivial fraction is to the left of the actual costs of $250 million, with the probability of only 0.0007 that the actual policy decision to control RIFA is wrong. Conditional on the unlikely event of costs exceeding benefits, benefits still average about 80% of the costs. Based on

FIGURE 2. Value of information as project cost changes



these considerations, one might expect the value of information to be essentially zero. Given the probability distribution of benefits, we can quickly evaluate that value by randomly sampling from the distribution and taking the sample average of formula (2). This calculation reveals that the value of resolving uncertainty about benefits is perhaps surprising large, about \$35,000.

A trivial chance of the decision being regrettable apparently does not imply a trivial value of information. While the chance of error is only 0.0007, the expected loss given an error is about \$50 million. As shown in formula (6), the VOI is the product of these two numbers: $0.0007 \times 50,000,000 = 35,000$. So, the absolute scale of the problem (in billions of dollars) is sufficient to generate a non-trivial VOI despite a very small chance that the policy is in error. In fact, the VOI is scales linearly in benefits and costs. Dividing the original benefits and costs by 100, a similar decision with a \$28 million expected benefit with a \$2.5 million cost would generate only about a \$350 VOI.

Holding the distribution of benefits fixed, one expects that increasing costs will increase the VOI, at least initially. Indeed, we find that hypothetically doubling costs to \$500 million increases VOI to about \$800 thousand, a factor of 23. This sharp rise can be attributed to the fact that the probability that the decision is regrettable grows proportionally very quickly with the value of C. Figure 2 displays the value of information as the expected control cost is hypothetically varied. We see that it rises very rapidly, with a convex shape up to a sharp peak, and then declines rapidly from that peak. Close examination of the numbers shows that the peak is at \$2.8 billion, which is exactly the expected benefits. At least in this hypothetical case, the value of information is maximized when the decision maker would be just indifferent between implementing and foregoing the control policy given only the prior information. In the next section, we examine the generality of these features.

3. Analysis

In this section, we analyse how the value of information changes with the uncertainty over the distribution of benefits and with the prior expected cost-benefit ratio. One practical payoff of this analysis is that it allows us to derive simple upper bounds on VOI when the decision maker is only able to specify some very crude properties of the prior. This may be particularly useful to decision maker when a prior is not yet well developed, when experts disagree on the proper prior, or when robustness against a range of possible priors is desireable. Having such a readily calculated and uncontroversial upper bound on VOI will, of course, prove quite useful if the costs of further study exceed the bound. In that case, the decision maker can optimally finalize the policy without further study or delay. If, however, the costs of further study are less than the bound, then a more precise prior must be developed or specified in order to determine whether it is optimal to invest in further information about the benefits (or costs) of a policy.

One feature of VOI suggested by basic intuition is that as uncertainty increases, the value of resolving that uncertainty cannot decrease. However, as Gould (1974) showed, the value of information may actually decrease as common measures of uncertainty such as variance or entropy increase. One measure of uncertainty that has found very wide application and acceptance is the notion of increased risk introduced by Rothschild and Stiglitz (1970). It is intuitively clear that adding mean-zero random noise to an uncertain variable increases its uncertainty. Adding such noise fattens the tails of the probability density function, without shifting the mean. Rothschild and Stiglitz demonstrate several useful features of this definition of increased risk. In particular, the expected value of any convex function of a random variable cannot be decreased by a mean-preserving spread of the random variable, a fact which generates our desired result.

Theorem 1. *A mean preserving spread in the prior increases (weakly) the value of information.*

Proof. Looking at formula (2), a mean preserving spread changes only the first term. The expression $\max(B - C, 0)$ is a convex and piece-wise linear function of B. Because it is convex, the theorem follows immediately from the results of Rothschild and Stiglitz. □

Our second basic result is that the location of the peak in Figure 2, where costs equals expected benefits, is a general result.

Theorem 2. *The value of information is maximized when the expected value, evaluated over the prior benefit distribution, of the program is zero.*

Proof. The result follows immediately from taking the derivative of VOI. When $\mathbf{E}_B\, B < C$ the VOI is given by formula (3), and its derivative with respect to C is non-negative. When $\mathbf{E}_B\, B > C$, the VOI is given by formula (5), and its derivative is non-positive. Since the VOI is non-decreasing when the expected cost-benefit ratio is less than one, and non-increasing when the cost-benefit ratio is greater than one, the claimed result follows. Further, evaluating the second derivatives show that the curve is convex to the left of the peak, and concave to the right of the peak. □

These simple theorems imply simple upper bounds on the value of information, given crude features of the prior. In particular, we assume the decision maker is willing to specify upper and lower limits, $\underline{B}$ and $\overline{B}$, on the plausible support for benefits. In many cases, the decision maker will also be able to specify a value for the prior expected benefit, $B^* = \mathbf{E}_B\, B$. If no further information could be gathered, the decision rests on whether $B^* > C$. So, if the decision maker is capable of answering this question for arbitrary value of C, a specific value of B^* is implied. Finally, in many cases it will be plausible that the distribution of benefits is single-peaked, possibly with the peak specified to be at the central tendency B^*.

In order to develop upper bounds on VOI for these various crude features, the general strategy is to first identify the maximally spread distribution consistent with those features. By Theorem 1, no other distribution with those features can have a higher VOI. The maximally spread distribution may not itself be particularly plausible, but it nevertheless serves the purpose of bounding an entire class of potentially plausible distributions. Below, we specify the maximally spread distribution for each of three cases, each of which takes a simple form. For each case, we analytically present the implied upper bound on VOI, though they could easily as would usually be done when the practioner if faced with some arbitrary distribution over benefits.

Further by exploiting Theorem 2, the same analysis provides bounds for the case where the analyst does not wish to specify either the prior expectation B^* of benefits or does not wish to specify costs. Either might be reasonable if the analyst wishes to see how robust a result is, for example if there is some controversy among stakeholders about the true values. Of course, the less information specified, the less tight the bounds are, so there is no free lunch. The trick here is that the maximal VOI occurs when $C = B^*$. The formulas developed below all depend on both C and B^*. If it happens that one does not wish to specify a particular value of B^*, then simply plugging in C where B^* occurs yields an upper bound on any possible value for B^*. Similarly, if it happens that one does not wish to specify C, them plugging in B^* where C occurs yields an upper bound on VOI for any possible value of C.

Case 1: Only the supports and the mean are specified, with no other restrictions.

The maximally spread distribution for this case has one mass point at each support. The weights on the two points are identified by two constraints: that probability integrates to one, and that the mean must be preserved. The probability mass at the upper support is $\frac{B^* - \underline{B}}{\overline{B} - \underline{B}}$.

The VOI bounds follow from direct application of formula (2) to this two mass-point distribution. If $B^* < C$, the VOI bound is

$$\frac{B^* - \underline{B}}{\overline{B} - \underline{B}}(\overline{B} - C) - \max(B^* - C, 0).$$

To illustrate the use of Theorem 2, it must also be the case that VOI is less than

$$\frac{C-\underline{B}}{\overline{B}-\underline{B}}(\overline{B}-C),$$

which follows from substituting in C for B^*. Similarly, it must be the case that VOI is less than

$$\frac{B^*-\underline{B}}{\overline{B}-\underline{B}}(\overline{B}-B^*).$$

which follows from substituting in B^* for C.

Case 2: In addition to the supports and the mean, the prior is constrainted to be single-peaked, with no most likely value specified.

The single-peak requirement forces the density to be continuous on the interior of the support. It is convenient notation to let $\tilde{B}$ indicate the midpoint of the support: $\tilde{B} = (\overline{B} - \underline{B})/2./$ The maximal spread requirement, combined with mean preservation, forces the peak to occur at $\underline{B}$ when $B^* < \tilde{B}$ and to occur at $\overline{B}$ otherwise.

When $B^* < \tilde{B}$, a probability mass of $\frac{\tilde{B}-B^*}{\tilde{B}-\underline{B}}$ occurs at $\underline{B}$. The remaining probability, $\frac{B^*-\underline{B}}{\tilde{B}-B^*}$, is uniformly spread over the full support. So, the continuous density is the constant $\frac{B^*-\underline{B}}{(\tilde{B}-B^*)(\overline{B}-\underline{B})}$. From (2), the VOI for this distribution is $\int_C^{\overline{B}}(B-C)f(B)dB - \max(B^*-C,0)$. Expanding out the integral in the first term yields the upper bound

$$\frac{(\overline{B}-C)^2(B^*-\underline{B})}{2(\tilde{B}-B^*)(\overline{B}-\underline{B})} - \max(B^*-C,0).$$

Similarly, when $B^* > \tilde{B}$, a probability mass of $\frac{B^*-\tilde{B}}{\overline{B}-\tilde{B}}$ occurs at $\overline{B}$. The remaining probability, $\frac{\overline{B}-B^*}{\overline{B}-\tilde{B}}$, is uniformly spread over the full support. Straightforward evaluation of the conditional mean yields the VOI bound

$$\frac{(\overline{B}-C)(B^*-\tilde{B})}{\overline{B}-\tilde{B}} + \frac{(\overline{B}-C)^2(\overline{B}-B^*)}{2(\overline{B}-\tilde{B})(\overline{B}-\underline{B})} - \max(B^*-C,0).$$

Case 3: In addition to the supports and the mean, the prior is constrained to be single-peaked, with B^* being the most likely value.

The single-peak requirement forces the density to be continuous on the interior of the support. The maximal spread requirement forces the density to be locally uniform to both the left and the right of B^*, but allows different weights on the two segments. The weights on the two segments are identified by two constraints: that probability integrates to one, and that the mean must be preserved. To satisfy these constraints, the probability that $B > B^*$ must be $w = \frac{\underline{B}+B^*}{\overline{B}+\underline{B}-2B^*}$. The probability density function is $w/(\overline{B}-B^*)$ over the range (B^* to $\overline{B}$) and the density is $(1-w)/(B^*-\underline{B})$ over the range ($\underline{B}$ to B^*). Call these two constants for the density f_R and f_L, with the subscripts indicating right and left respectively.

When $C > B^*$, only the part of the density to the right of B^* enters the calculation. In this case, again by straightforward calculation of formula (2), the VOI upper bound is

$$f_R(\overline{B}-C)^2/2 - \max(B^*-C,0).$$

When $C < B^*$, the formula is slightly more complicated, since it must account for both segments of the density. In this case the VOI bound is

$$f_R(\overline{B}-C)^2/2 + (f_L-f_R)(B^*-C)^2/2 - \max(B^*-C,0).$$

References

Arrow, K. and A. Fisher (1974). Environmental preservation, uncertainty, and irreversibility. *The Quarterly Journal of Economics 88*(2), 312–319.

Australian Government (2007, 20 April). Record and resolutions. Twelth Meeting of Primary Industries Ministerial Council.

Conrad, J. (1980). Quasi-option value and the expected value of information. *The Quarterly Journal of Economics 94*(4), 813–820.

Gould, J. (1974). Risk, stochastic preference, and the value of information. *Journal of Economic Theory 8*(1), 64–84.

Kompas, T. and N. Che (2001). An economic assessment of the potential costs of red imported fire ants in Australia. Report for Department of Primary Industries, Queensland.

Lawrence, D. (1987). The assessment of the expected value of information in the binary decision model. *Managerial and Decision Economics 8*(4), 301–306.

Lindhjem, H. and S. Navrud (2008). How reliable are meta-analyses for international benefit transfers? *Ecological Economics 66*(2-3), 425–435.

Marschak, J. (1954). Towards an economic theory of organization and information. In *Decision Processes*, pp. 187–220. New York: Wiley.

McCubbin, K. and J. Weiner (2002). Fire ants in Australia: a new medical and ecological hazard. *The Medical journal of Australia 176*(11), 518.

Raiffa, H. and R. Schlaifer (1961). *Applied statistical decision theory.* Boston: Harvard University Graduate School of Business Administration.

Rothschild, M. and J. Stiglitz (1970). Increasing risk: I. A definition. *Journal of Economic Theory 2*(3), 225–243.