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by

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Some Issues in Dealing with Risk in Agriculture*

J Brian Hardaker**

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Introduction

Risk in agriculture, as in life, is everywhere. But dealing with it systematically, whether for farmers, researchers or anyone, is difficult. One reason for the difficulty is confusion and differences of opinion about what risk is and how it can be measured. The first purpose of this paper, therefore, is to offer some suggested answers to these questions. Then some approaches to the analysis of risky choices are canvassed, particularly in the context of agricultural production systems. Matters considered include how to estimate risk aversion among target groups of farmers, how to derive and refine probabilities to describe relevant uncertainty, and how to integrate these components into risk analyses.

Risk analysis has become increasingly popular in recent years. Unfortunately, some analysts have been rather cavalier in the way that they have applied the theory and methods of decision analysis. Given the complexity of risk analysis it is hardly surprising that some mistakes have been made and that there is scope for disagreement on how to proceed.. A second objective of this paper, therefore, is to identify some of the main areas of difficulty and possible confusion and to suggest more theoretically sound concepts and practicable methods.

Defining risk

Even supposed experts use the term ‘risk’ in several different ways. These differences cause considerable confusion especially when systematic efforts are made to measure risk and to evaluate it. Among the many usages of the word, three common interpretations are:

1. the chance of a bad outcome;
2. the variability of outcomes, i.e. the converse of stability; and

3. uncertainty of outcomes.

Although seemingly similar, these three definitions imply quite different ways of measuring risk. Moreover, when formally defined they can be seen to be mutually inconsistent. It will be argued here that, while the first two meanings are in common usage, clarity is best served by defining risk, at least for formal analyses, as the uncertainty of outcomes.

Measuring risk

Let's look at each of the above definitions in turn to see how risk might be measured for each.

'The chance of a bad outcome' implies the probability of some defined unsatisfactory outcome happening. Assume for simplicity that there is a single measure of outcome, X, more of which is always preferred to less. This definition of risk might be represented by the probability $P^* = P(X \leq X^*)$, where P is probability, X is the uncertain outcome, and X^* is some cut-off or minimally acceptable outcome level below which outcomes are regarded as 'bad'. In some cases, the value of X^* might reflect some disaster level such as 'starvation' or 'bankruptcy', but in most cases it may be a less clear-cut notion, so that application of this measure of risk requires specification of the two parameters P^* and X^*.

Risk as variability may be measured by some statistic of dispersion of the distribution of outcomes, such as the variance or standard deviation of X, $V = V[X]$ or SD, equal to the positive square root of V. Obviously, neither statistic alone tells anything about the location of the distribution of outcomes on the X axis. So it is common for those who think of risk as dispersion of outcomes to link V or SD with the mean or expected value $E = E[X]$. Then variance may be described as the risk around the specified mean. Building on this notion, some authors, such as Newbery and Stiglitz (1981), have found it convenient to reflect risk using the coefficient of variation of X, $CV = SD/E$.

Finally, adopting the definition of risk as the distribution of outcomes requires the whole distribution of X to be specified. Complete specification requires the probability density function, $f(X)$, or equivalently and often more conveniently, the cumulative distribution function $F(X)$. However, summary statistics including moments are commonly used to describe the probability distribution, implying some similarity with the measurements based on the definition of risk as dispersion. For a few special cases, such as the normal, the distribution of outcomes is fully defined by only the mean and variance. Other distributions might be approximated in terms of these first two moments, though higher order moments may be needed to tell more about the shape of the distribution. For some arbitrary distribution, however, description by moments will be an approximation the adequacy of which is not easily judged.[1]

The weakness of the first two definitions of risk with their associated measures is that neither 'tells the whole story' when a choice has to be faced amongst risky alternatives. In regard to the first definition, it is clear from observing behaviour that not all risks with bad outcomes

[1] Note that some of the usual statistical tests of normality may be misleading in that small deviations in, say, the location of the lower tail of the distribution compared with the normal may be discounted in the test, but may be very important to a risk-averse decision maker.

are rejected. For example, most people will travel by car for sightseeing—an activity that certainly increases the probability of death or serious injury in a road accident. Evidently, choices with chances of very bad outcomes (e.g. death or serious injury) are sometimes accepted, presumably because the benefits of the up-side consequences (e.g. seeing interesting sights) are sufficiently appealing to offset the relatively low chances of the bad outcome. It follows that to evaluate or assess a risk we need to be able to consider the whole range of outcomes, good and bad, and their associated probabilities. Descriptions of risk expressed in terms of only the probability in the lower tail of the distribution of outcomes do not provide full information for proper risk assessment, and so may be seriously misleading.

A similar argument shows the limitation of variance alone as a measure for risk evaluation. Consider two normal distributions of outcomes of, say, net income, with identical variances but different means. Everyone will prefer the one with the higher mean. Moreover, many would describe the distribution located further to the right as the less risky of the two since the chance of getting less than any specified level of X is lower for this distribution than for the one with the lower mean.[2] On the other hand, using variance as the measure of risk suggests that the two distributions are equally risky. Clearly, we could avoid such confusion by interpreting measures of dispersion or stability simply as what they are, and not regarding them as 'stand alone' measures of risk.

If risk is defined as variance but is always interpreted in conjunction with the mean, this definition might seem to be similar to defining risk as the distribution of outcomes but then using an E,V approximation of the distribution. But the problem inherent in defining risk as variance already noted still remains. Not all shifts in E,V space that reduce variance will lead to more preferred E,V combinations for a risk-averse decision maker (DM); if both E and V are reduced, the effect on preference is indeterminate unless the degree of risk aversion is known. Hence, it seems unwise and potentially confusing to describe every prospect with lower variance as ‘less risky’.

Adopting the third option of defining risk as the full distribution of outcomes means that there is no one statistic that can be used to measure risk, so that it becomes impossible to compare distributions in terms of their ‘riskiness’. While this might seem to make the notion of risk elusive, in fact, the absence of such a single measure proves to be no impediment to the comparative assessment of alternative risky prospects, as discussed below. What this third view of risk implies is that notions of ‘more’ or ‘less’ risk (‘more risky’ versus ‘less risky’ prospects) are unsatisfactory, and careful analysts will confine themselves to describing risky prospects as ‘preferred’ versus ‘not preferred’, or as ‘risk efficient’ versus ‘not risk efficient’.

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[2] Pandey (personal communication) has shown that, for the normal distribution, the coefficient of variation is equivalent to the measurement of risk as the probability of a ‘bad’ outcome, provided the safety-first level of outcome is near to zero. For the two normal distributions mentioned, the one to the right obviously has the lower CV and also the lower probability of an outcome less than zero (or any other value).

Assessing risky alternatives

There is a good reason why none of the conventional statistical measures of a distribution can provide a full description of the entailed risk. As the example of car travel for sightseeing shows, risk assessment requires both probabilities and preferences for outcomes. Chances of bad versus good outcomes can only be evaluated and compared knowing the DM's relative preferences for such outcomes.

According to the subjective expected utility (SEU) hypothesis (Anderson, Dillon and Hardaker, 1977, pp. 66-69; Savage 1954)) the DM's utility function for outcomes is needed to assess risky prospects. The SEU hypothesis states that the utility, or index of relative preference, of a risky prospect is the DM's expected utility for that prospect, meaning the weighted average of the utilities of outcomes. This index is computed using the DM's subjective probabilities for outcomes as weights and using the DM's utility function to encode preferences for outcomes. Faced with a choice amongst alternative risky prospects, the hypothesis is that the prospect with the highest expected utility is preferred.

The expected utility of any risky prospect can be converted through the inverse utility function into a certainty equivalent (*CE*). Ranking prospects by *CE* will be the same as ranking them by expected utility, i.e. in the order preferred by the DM. Moreover, the difference between the *CE* and the expected value of a risky prospect, known as the risk premium (*RP*), is a measure of the cost of risk:

$$RP = E - CE. \qquad (1)$$

For risk-averse DMs, *RP* will be positive and its magnitude will depend on both the distribution of outcomes and the DM's attitude to risk.

For some uses it may be convenient to compute the proportional risk premium, *PRP*, defined as:

$$PRP = RP/E, \qquad (2)$$

i.e. the proportion of the expected value of the risky project absorbed by the risk premium in computing the *CE*. The more risk averse is the DM or the more uncertain the risky prospect, the higher will be the *PRP*.

In relation to the earlier discussion of the problems of defining and measuring risk, the *CE* may be taken to be a measure of risk efficiency, meaning that a risky prospect with a higher *CE* will be preferred to one with a lower *CE*. On the other hand, while *RP* and *PRP* measure the actual and proportional costs of risk, respectively, they should not be taken to measure risk *per se*; since *CE* depends on both *E* and *RP*, considering only the latter term can lead to similar confusion as can arise in treating *V* alone as a measure of risk.

Moreover, as we shall see later, risk aversion itself is an elusive concept that depends on the context. In particular, we need to be very clear about what measure of outcome is being used.

Risk aversion and the utility function

The above discussion shows that risk cannot be assessed without accounting for the risk attitude of the DM. According to the SEU hypothesis, risk preference is reflected in the

DM's utility function for consequences. The shape of such a utility function specifies an individual's attitude to risk. Several attempts have been made, therefore, to elicit such utility functions from farmers in order to put the SEU hypothesis to work in the analysis of risky prospects in agriculture. Usually the results have been rather unconvincing. There is evidence that the functions obtained are vulnerable to interviewer bias and to bias from the way questions are framed.

Some of the difficulties in utility function elicitation may be reduced by wise choice of the measure of outcome. It is clear, for example, that people assess losses and gains differently from how they view, say, income or wealth. This seemingly irrational behaviour is called 'failure in asset integration', or 'the endowment effect', and raises the question of what to do about it. For normative decision analysis, it does not seem sensible to base recommendations on such seemingly inconsistent preferences.

Plausible utility functions are most often obtained from elicitation of the utility of wealth, and it seems likely that utility functions for income will often be more convincing than those for losses and gains. However, these sorts of suppositions need to be tested as part of the further consideration of the practicality of 'full-blown' implementation of the SEU hypothesis in agricultural decision analysis.

The truth is, however, that few people are able to articulate their risk preferences consistently. Some efforts have been made to circumvent the elicitation difficulties by estimating risk aversion from observed behaviour, usually using cross-sectional data. While these methods certainly cannot be dismissed, given the lack of success of more direct methods, they all suffer from the fundamental weakness of being based on the assumption that the farmer and the analyst share the same probabilities about the risky phenomena at issue. In so far as this assumption is invalid, the results will be biased. Too, errors in model specification tend to be rolled into the estimated risk aversion coefficient, causing further bias.

Measures of risk aversion

For simplicity, we start by assuming that we are assessing risk aversion in respect of the DM's wealth, i.e. that there is an actual or implicit utility function $U = U(W)$. Later we consider the implications of utility expressed in terms of other measures such as income or losses and gains.

Because of perceived difficulties in getting empirical measures of risk aversion, it may be necessary to make some strong assumptions about the degree of risk aversion of farmers if any analysis of risk is to be performed. However, measuring degree of risk aversion is not simple for a couple or reasons. First, a utility function is defined only up to a positive linear transformation. Any measure of risk aversion, which is essentially a measure of curvature of the utility function, must remain constant for such a transformation. Second, as noted above, we need to be clear about what is the argument of the utility function.

The simplest measure of risk aversion that is constant for a positive linear transformation of the utility function is the absolute risk aversion function:

$$r_a(W) = -U''(W)/U'(W) \quad (3)$$

where $U''(W)$ and $U'(W)$ represent the second and first derivatives of the utility function, respectively (Arrow 1965, p. 33; Pratt 1964). It is generally accepted that $r_a(W)$ will decrease with increases in W.

Absolute risk aversion is a much used and abused concept. First, note that it is a function, not a constant, as is often implied. Moreover, although robust enough to be unaffected by a positive linear transformation of the utility function, absolute risk aversion is still measured in the monetary units of W. Thus, risk aversion coefficients derived in different currency units are not comparable. It is invalid to transport a coefficient estimated for US farmers in US dollars to an analysis of an Australian farm management problem where outcomes are expressed in Australian dollars or worse, thousands of dollars of Australian dollars.

The currency units problem is overcome using the concept of relative risk aversion, defined as

$$r_r(W) = Wr_a(W) \qquad (4)$$

This measure of risk aversion is a pure number which can be used in international comparisons of risk aversion, only remembering that, like $r_a(W)$, $r_r(W)$ is a function, not a constant. While there is general agreement that $r_a(W)$ declines as wealth increases, there is less agreement on how $r_r(W)$ is likely to be affected by increases in wealth. Arrow (1965, p. 36) argues on theoretical and empirical grounds that it would generally be an increasing function of W. However, he noted that some flutuations are possible, but suggested that the actual value should hover around 1, being, if anything, somewhat less for low wealths and somewhat higher for high wealths. Similarly, Eeckhoudt and Gollier (1992, p. 46) hypothesised that, if wealth increases, relative risk aversion does not decrease. On the other hand, Hamal and Anderson (1982) found that, in extremely resource-poor farming situations, relative risk aversion could reach values as extreme as four or more – quite contrary to what Arrow had hypothesised. Such disagreement might be taken to indicate that $r_r(W)$ is likely to be more constant than $r_a(W)$ as W changes.

Obviously, the choice of any particular form of utility function has implications for $r_a(W)$ and $r_r(W)$. For example, the widely used negative exponential function $U = 1 - \exp(-cW)$ has the property that $r_a(W)$ is equal to the constant c (constant absolute risk aversion - CARA) and the seemingly unlikely property of increasing relative risk aversion. On the other hand, the power function $U = W^c$, $0 < c < 1$ has decreasing absolute risk aversion (DARA) and constant relative risk aversion (CRRA). The power function reduces to $U = \ln(W)$ when $r_r(W) = 1$. A special form of the CRRA power function that has significant operational advantages is $U = \{1/(1 - r)\}W^{(1 - r)}$, where r is the constant relative risk aversion coefficient.

Constant absolute risk aversion means that preferences amongst risky prospects are unchanged if a constant amount is added to or subtracted from all payoffs. Constant relative risk aversion means that preferences are unchanged if all payoffs are multiplied by a positive constant.

Plausible assumptions about risk aversion

In the past, it has been common to assume, often implicitly, that all farmers are indifferent to risk. Such an assumption is necessary to justify the many farm management budgets that are done with no accounting at all for risk. Such an assumption seems to be a second-best option when we know that risk aversion is widespread. A more sensible course, if there is no other information at all, might be to assume a relative risk aversion coefficient of 1.0. The constant relative risk averse function for $r = 1$ is $U = \ln(W)$, the so-called 'everyman's' utility function postulated by Daniel Bernoulli as long ago as 1738.

If this seems to be too strong an assumption, Anderson and Dillon (1992) have proposed a rough and ready classification of degree of risk aversion, based on the magnitude of the relative risk aversion coefficient, that some might find plausible. Their classification is:

$r_r(W)= 0.5$: hardly risk averse at all;

$r_r(W) = 1.0$: somewhat risk averse (normal);

$r_r(W) = 2.0$: rather risk averse;

$r_r(W) = 3.0$: very risk averse;

$r_r(W) = 4.0$: extremely risk averse.

The estimates of risk aversion might to validated to some extent by constructing a representative risky prospect, computing its CE using the CRRA function with r_r equal to the tentatively chosen value, and then asking the DM whether the implied indifference between the risky prospect and the sure thing seems reasonable.

If $r_a(W)$ is needed, and if it is assumed that $r_r(W)$ is more or less constant for local variation in wealth, $r_a(W)$ may be derived using the formula $r_a(W) = r_r(W)/W$.

Such approximations might be made for some target group of farmers in the work of research stations and extension agencies, leading to an estimate of the range of r_a that might be plausible. This range can be used in risk analysis for such specific contexts.

Utility of what? The effect of choice of payoff measure

So far, we have considered utility and risk aversion only in terms of wealth. What happens when we move to outcomes measured in other ways, such as in terms of income or losses and gains? Consider the latter first. A loss or gain can be viewed as simply a change in wealth of the person experiencing that loss or gain. We can write:

$$\tilde{W} = W_0 + \tilde{X} \tag{5}$$

where W is wealth after the event, W_0 is initial wealth and X is the loss or gain. If we assume that either W_0 is known for sure or that X and W_0 are stochastically independent[3], then we should expect a rational person to make the same choice whether the risky outcomes are expressed in terms of wealth or gains/losses.

Unfortunately, empirical evidence does not support this proposition. Typically, we find that people are much more risk averse when asked to contemplate gains and losses than they are if the same risky prospect is presented to them in terms of wealth. The effect is know as failure in asset integration because gains and losses are not intuitively integrated into a wealth

[3] These assumptions may be too strong in some cases. We consider later the case where an additional risky prospect is added to an existing risky portfolio with stochastic dependency between the two.

assessment. Such behaviour can be argued to be irrational and in what follows we assume that a rational person who wants to make wise risky choices would be prepared to use logic rather than intuition to derive implications for choices expressed in gains/losses from a carefully chosen utility function for wealth.

Recall that constant absolute risk aversion means that preferences are unchanged if a constant is added to or subtracted from all payoffs – the exact situation we have here. Therefore, if we do not want preference to change whether we express outcomes in terms of W or X, we can specify that $r_a(W) = r_a(X)$. Then, as before, $r_r(W) = Wr_a(W)$ so $r_a(W) = r_r(W)/W$. Moreover, $r_r(X) = Xr_a(X)$ by definition, but $r_a(X) = r_a(W)$ so

$$r_r(X) = Xr_a(W) = (X/W)r_r(W) \tag{6}$$

In other words, in assessing risky choices expressed in terms of losses and gain, it is not correct to apply the same relative risk aversion coefficient as for wealth. Moreover, the smaller is X relative to W, the smaller is the applicable relative risk aversion coefficient. The relative risk aversion function $r_r(X)$ in equation (6) is also sometimes called the partial risk aversion function since it refers to only part of the payoff as shown in equation (5).

Now let's consider risky choice where payoffs are expressed in terms of income. At least two types of risky choices affecting farm income can be imagined. One is where the income next year (or in some single year in the future) is uncertain. This is the typical situation when doing annual farm planning. The uncertainty in the outcomes stems largely from the year to year unpredictability yields, prices and costs that affect farmers' incomes. This type of uncertainty contrasts with longer term uncertainty as when a farmer may be contemplating a major investment perhaps associated with a dramatic change to the farming system. Here the uncertainty is about the long-run level of income. The distinction between the two is similar to the distinction Friedman (1957) drew between *permanent income* and *transitory income* in his work on the consumption function.

Drawing further on Friedman's ideas, it seems clear that transitory income can be treated in decision analysis rather like losses and gains. We could write:

$$\tilde{W} = W_0 + \tilde{y} - c_p \tag{7}$$

where y is transitory income and c_p is Friedman's permanent consumption, assumed constant. Defining $X = y - c_p$ converts equation (7) into equation (5), so the matter will not be pursued further since identical conclusions apply as for risk aversion with payoffs as losses and gains.

Now consider what happens when it is long-run or permanent income that is risky and the focus of attention. It seems reasonable to assume that a rational person will view their wealth as equal to the capitalised value of future (permanent) income flows with the capitalisation factor calculated over expected future lifetime.[4] In that case we can write

$$\tilde{W} = k\tilde{Y} \tag{8}$$

[4] The income stream may also include a terminal value of assets, if an individual sees it as important to leave assets for their descendants.

where W is current wealth, Y is the annual permanent after-tax income and k is the appropriate capitalisation factor, $k > 1$. Then, since wealth is viewed as a fixed multiple of income (and vice versa), a rational individual will assign the same proportional risk premium to a given risky prospect whether the payoffs are expressed in wealth or in terms of the equivalent permanent income. This is equivalent to the proposition that

$$r_r(W) = r_r(kY) = r_r(Y) \tag{9}$$

where $r_r(.)$ is the relative risk aversion function.

Since $r_a(W) = r_r(W)/W$ and $r_a(Y) = r_r(Y)/Y$, then $r_a(Y) = r_r(W)/Y$ or

$$r_a(Y) = (W/Y)\, r_a(W). \tag{10}$$

Finally, since $k = W/Y$ from equation (8), then $r_a(Y) = kr_a(W)$. In other words, $r_a(Y)$ is k times as large as $r_a(W)$ where k is the relevant capitalisation factor of approximate magnitude 10.

By way of postscript to the above discussion of the effect of choice of argument of a utility function on risk aversion, it should have become apparent that there are likely to be very substantial difficulties in inferring anything about the appropriate degree of risk aversion if payoffs are expressed in other ways than those canvassed above. It becomes very hard indeed to see how the appropriate degree of risk aversion can be derived for such measures as gross margin per hectare of crop, per kilogram of milk produced or per dollar invested. Still worse are attempts to derive the appropriate degree of risk aversion for compare distribution of, say, crop yield per hectare. Yet it is not unusual to come across examples of results expressed and analysed in just such partial terms.

The importance of risk aversion

An indication of the implications for risky choice of different degrees of risk aversion can be obtained from the approximation (Freund 1956):

$$CE = E - 0.5r_aV \tag{11}$$

where CE is certainty equivalent, E is expected payoff, r_a is the appropriate absolute risk aversion coefficient (assumed constant) and V is variance of payoff.[5] Then the approximate risk premium, RP, is given by

$$RP = E - CE = 0.5r_aV. \tag{12}$$

Multiplying through by E/E^2 gives the proportional risk premium PRP, representing the proportion of the expected payoff of a risky prospect that a DM would be willing to pay to trade away all the risk for a sure thing:

$$PRP = RP/E = 0.5r_aE(V/E^2) = 0.5r_rC^2 \tag{13}$$

[5] The relationship is exact for the negative exponential utility function with constant absolute risk aversion if the returns are normally distributed (Freund). For other cases the approximation may be derived as a truncated Taylor series expansion omitting terms after the second. The omitted terms incorporate products of successive derivatives of the utility function and successively higher-order moments of the utility function.

where C is the coefficient of variation of the risky prospect, equal to the standard deviation divided by the mean. For example, if $r_r = 2$ and $C = 0.2$, PRP = 0.04. Similarly, if $r_r = 4$ and $C = 0.3$, $PRP = 0.18$. Note, however, that, for reasons explored above, magnitudes of r_r such as 2 or 4 are only likely to apply for risky prospects expressed in terms of permanent income or total wealth.

The impact of risk aversion will be different to the above for DMs assessing a marginal additional risky prospect (Anderson 1989). If such a marginal risky prospect is evaluated in terms of gains and losses, X, relative to initial wealth W_0, now treated as uncertain, the relevant risk premium is

$$RP[X] = 0.5r_a\Delta V \tag{14}$$

where

$$\begin{aligned}\Delta V &= V[X] + V[W_0] + 2Cov[X, W_0] - V[W_0] \\ &= V[X] + 2\rho S[X]S[W_0]\end{aligned} \tag{15}$$

where Cov is covariance, ρ is the relevant correlation coefficient and S is standard deviation. (In equation (1) we assume that $r_a(X) = r_a(W_0) = r_a(W) = r_a$, i.e. a constant, as in equation (11).) Thus the risk deduction as a proportion of $E[X]$ is

$$\begin{aligned}PRP_X &= 0.5r_aE[X]\{V[X]/E[X]^2 + 2\rho S[X]S[W_0]/E[X]^2\} \\ &= 0.5r_p(X)\mathrm{C}[X]^2 + r_p(X)\rho C[X]S[W_0]/E[X]\end{aligned} \tag{16}$$

where r_p is partial risk aversion for gains or losses defined as:

$$r_p(X) = r_a(W_0)X = E[X]/E[W_0]\ r_r(W_0) = Zr_r(W_0) \tag{17}$$

with $Z = E[X]/E[W_0]$. However, since $E[X] = ZE[W_0]$, the proportional risk deduction for X can be written as:

$$\begin{aligned}PRP_X &= 0.5\ r_p(X)C[X]^2 + r_p(X)\rho C[X]C[W_0]/Z \\ &= 0.\ 5r_r(W_0)ZC[X]^2 + r_r(W_0)\rho C[X]C[W_0] \\ &= r_r(W_0)C[X]\{0.5ZC[X] + \rho C[W_0]\}.\end{aligned} \tag{18}$$

By way of illustration, Hardaker, Huirne and Anderson (1997) give the case for $r_r(W_0) = 1.0$, $C[X] = 0.3$, $Z = 0.1$, $\rho = 0.5$ and $C[Y] = 0.2$, yielding a value for PRP_X of 0.035. In other words, for the values indicated the DM would be willing to sacrifice only 3.5 per cent of $E[X]$ to avoid the associated additional variance. The same authors show the value of PRP_X for a range of other plausible values of the variables, mostly indicating that the additional risk aversion is relatively small.

As shown by equation (18) and illustrated above, the cost of risk may be a small proportion of the expected value for some transiently risky prospect that constitutes only a part of the risk faced by a farm household. While it is an empirical matter, many such marginal risks in diversified agricultural systems may have near-zero values of PRP, so that choices can be based on expected values alone. Even when PRP values are somewhat larger, the ranking of alternatives based on expected payoffs may be the same as that based on expected utility. At least, this seems likely in such matters as the choice among alternative crop varieties to be used on just part of the farm when the alternatives may have broadly similar yield stability characteristics but significantly different mean yields. Moreover, even when the ranking of marginal risky prospects based on expected values differs from that based on expected utility or certainty equivalents, the cost of making the wrong choice using the expected value rule may be low in *CE* terms.

If empirical testing shows the costs of risk to be small for a range of actual farm situations, it is good news for scientists who can focus more intently on developing technologies that improve expected returns without worrying too much about stability.

More generally, because in many practical choice situation the cost of risk may be relatively small, it can be argued that agricultural economists have paid too much attention to risk aversion, at least relative to efforts to get good specifications of the probability distributions of outcomes. If these distributions are mis-specified, the estimate of *E* will be biased, which may matter more than the error in calculating *RP* due to using the wrong risk aversion coefficient. Moreover, the focus on risk aversion and the cost of risk may have been a source of confusion in that attention has been directed to reducing the cost of risk rather than on finding the most risk-efficient option (erroneously minimising RP rather than maximising *CE*).

Such mistaken emphasis on risk reduction may come from analyses of risk from a policy perspective where risk can be viewed as a friction to resource allocation by farmers. Risk aversion may lead farmers to use resources less intensively than would be the case if they were indifferent to risk, at least for decisions important to them. Yet, from a social welfare perspective, most risks faced by individual farmers or groups of farmers are very unimportant. This is evident from equation 8 applied to a farm-level risk in a social setting; in that case *Z* will be small since national income from other sources will be large, and the relevant correlation will be small because of the diversified nature of the rest of the economy. It therefore becomes a potentially legitimate role of public policy to consider the scope to reduce the cost of risk to farmers in order to reduce the social welfare loss from farm-level risk aversion. It is, of course, quite another matter to decide whether interventions to reduce such welfare losses are justified. Given the high information needs and the likely difficulty and high cost of devising appropriate interventions, the chances are that, in most cases, governments should leave well alone. This view is reinforced by the point argued earlier in this section that, for many farm-level decisions, the risk friction might well be less than seems to be widely believed.

Probabilities for decision analysis

Both the SEU hypothesis and common sense lead to the conclusions that the right probabilities to use for decision analysis are the DM's subjective probabilities. A subjective probability may be defined as the degree of belief that an individual has in a given proposition. Many people have difficulty in coming to terms with such a 'subjectivist' view of the world, especially those who have been trained in the 'objectivist' school of thought in which probability is defined as the limit of a relative frequency ratio. It is worth emphasising, therefore, that Savage (1954) has elegantly synthesised the strands of expected utility and subjective probablility. However, this is not the place seek to convince the unconverted of the merits of the subjectivist view. Moreover, fortunately, the gap between the two schools of thought need not be as wide as these different definitions may seem to imply.

Taking a subjectivist view of probability, it is clear that, if faced with some risky choice, a rational person will seek to make his or her probability assessments as reliable as possible. This means he or she will want to gather evidence about the uncertain phenomena of interest until, in some approximate sense, the marginal cost of further information gathering rises to equal marginal benefit. Moreover, such a person will be particularly on the lookout for relevant relative frequency data to guide subjective probability judgment. If abundant and relevant data exist, the evidence will swamp any prior subjective beliefs, and there will be no practical difference between the probabilities used by a member of the objectivist school and a subjectivist.

Differences obviously come more into prominence when relevant data are few or absent—an all too common case. Here, according to the subjectivist, it is still possible for the analysis to proceed relying on the wholly or predominantly subjective probabilities of the DM. Unfortunately, however, that presents some difficulties for research and extension organisation for whom it is seldom possible to tailor recommendations to match the beliefs of individual farmers. Clearly, something more 'objective' would be desirable, especially in undertaking analysis intended to be of widespread relevance and acceptability.

Probabilities that have been derived based on thoughtful analysis of all relevant information can be described as 'public' probabilities, in the sense that many people might be willing to accept them as reasonable. Such public probabilities are the ones that could sensibly be used in analyses of, say, the risks of technology adoption in a given farming system. They can form the basis of at least tentative recommendations to farmers about what technologies appear to be risk efficient, although, of course, the probabilities are likely to be revised as more information comes available from accumulating experience with a technology.

Getting better probabilities

Getting 'better' probabilities when hard data are few or absent is no easy task, and considerable ingenuity and judgment are needed to make the best of a bad job. The topic is a sadly neglected one in the literature of agricultural economics. We suggest that there is a need to work towards a 'code of best practice', meaning that the approach to deriving probabilities should be based on careful thought and debate about what is reasonable in various types of situations.

Some rules of such a code, if ever properly developed, might include the following:

- Take pains to seek out and make good use of such relevant data as exist.
- On the other hand, never thoughtlessly use historical data that are not temporally and spatially relevant. For example, data from the past (where all historical data come from) may not be a good basis for making decisions about the future if the world has changed. Data of dubious relevance may need to be adjusted for any obvious bias, supplemented with more subjective judgments, or even ignored entirely.
- Where data are sparse, unreliable or of limited relevance, examine the costs and benefits of collecting more good-quality data for the assessment task at hand.
- As new data are accumulated, incorporate them appropriately into the probability judgments; Bayesian procedures will sometimes be helpful here in ensuring consistency.

- In the absence of hard data, make use of the views of people who should know best about the uncertain processes of interest.
- When consulting such experts, use more than one, and select people who will bring different insights to the estimation. Then use a sound method (such as Delphi) to seek convergence towards a consensus.
- Take steps to avoid biases in probabilities, however obtained. Where bias is suspected, consider and apply the best method you can devise to correct for the bias.
- Use smoothing methods to minimise implausible irregularities in distributions. Most distributions are smooth and unimodal. This observation suggests that best practice will require extensive use of the fractile rule to estimate points on the CDF, and then use of some procedure to smooth the curve through the obtained points (Anderson, Dillon and Hardaker, 1977, pp. 42-44). Smoothing will usually be vital for sparse data situations, but also makes sense in many situations with relatively abundant data. Not smoothing is equivalent to asserting that you expect the underlying distribution from which future outcomes are drawn to have the same 'bumps' present as displayed in the historical data, which is seldom likely.
- Avoid forcing probabilities to fit some pre-determined functional form unless there are good reasons to presume that that form is really appropriate. Experience with the software for fitting distributions to data points suggests that smoothing by eye is nearly always better than forcing the distribution to fit some standard form, such as the normal. Of course, that is not the case if there is some good reason to suppose that the process generating the distribution will lead to a particular form of distribution.
- Use 'triangulation' whenever practicable to compare probabilities for the same uncertain quantity obtained from different sources or in different ways.
- Take care to recognise and account for at least the main sources of risk affecting the outcomes of some risky prospect. In particular, avoid the trap of assuming that 'everything goes according to plan' (EGAP) when Murphy's Law and common experience both teach that such persistent good fortune is rare. Predicting the expected output of nonlinear stochastic systems by using the mean or modal values of stochastic input variables is a widespread EGPA error.
- Take care not to overlook important stochastic dependencies in obtaining probabilities for more than one uncertain quantity.
- Make the assessment process transparent—always tell what you did.

In Hardaker, Huirne and Anderson (1997) some of these ideas are developed a little further. For example, a procedure to transform historical information on farm activity net revenues into a representation of the relevant joint distribution for use in planning is described and illustrated. Sources of bias in human probability assessments are illustrated and the use of proper scoring rules to train experts to be less biased is described.

If the notion of a code of best practice applied to probability assessment seems far-fetched, it is worth pointing out that probabilities are necessary only because knowledge about the world is imperfect. All inquiry, including all agricultural research, can be viewed as human efforts aimed at adding to knowledge, i.e. towards the refinement of prior probabilities that may have been based on anything from ‘the wisdom of the ages’ through unsubstantiated supposition to pure superstition. Therefore, all the methods of systematic inquiry, including the so-called ‘scientific method’, can be seen as part of a tacitly accepted code of practice for upgrading probability judgments.

On methods of risk analysis

Modern computer software has revolutionised the scope for risk analysis. Packages such as DATA from TreeAge and Precision Tree from Palisade have made the construction and analysis of decision trees much easier. But probably of more general applicability in agricultural risk analysis is the @Risk add-in to spreadsheets such as Excel. Recent versions of @Risk for Excel seems more reliable than previous versions and are certainly easier to use.

Using this software, quite refined stochastic budgets can readily be constructed. Such budgets can also be viewed and used as stochastic simulation models. The software allows key variables in the model to be specified as uncertain quantities with defined probability distributions. There is a wide choice of form for such distributions. Stochastic dependency between variables can be approximated using rank correlation coefficients (or can be built in to the model by the analyst in other ways). Once completed, the model is run for a sufficient number of iterations using Monte Carlo sampling for the specified stochastic input variables in order to provide information about the distributions of selected output variables.

Such models can readily be used in farming systems work to evaluate alternative risky prospects, such as improved technologies. Experiments can be designed and implemented to compare alternative ‘treatments’, such as with versus without the prospective technology. If the DM’s utility function is known, treatments can be compared in terms of calculated *CE* values. If the utility function is not known but something can be inferred about the relevant range of risk attitudes, the treatments can be partitioned into dominated and efficient sub-sets. In some cases, the efficient set may contain only one prospect, indicating the optimal choice. When the set contains more than one risky prospect, the final choice must be a matter for the DM, or for each individual DM where the analysis is being performed for some target group.

Methods of performing such risk-efficiency analysis are particularly important for the work of agricultural research and extension organisations. They include mean-variance analysis, stochastic efficiency analysis, and particularly stochastic dominance with respect to a function (SDRF), and are sufficiently well known not to require further discussion here.

Stochastic budgeting can be extended to represent dynamic aspects of the risky systems being studied. However, if system dynamics lie at the core of a particular analysis, other powerful software is available to help. The package Stella II (and some other similar packages) allows the dynamics of any system to be represented as a simulation model that is developed first on screen in flow-chart format. Later, the underlying relationships can be quantified and the system run in dynamic fashion to observe performance. It is possible to include relevant stochastic components in the model, using Monte Carlo methods, to generate distributions of output variables. Stella II runs well on modern PCs.

The computer and software revolution has also brought the capacity to solve linear and nonlinear programming models to the risk analyst's desktop. Using GAMS, farming systems can be modelled in the constrained optimisation framework of mathematical programming, maximising some representation of expected utility. Such formulations also allow the risk-efficient set of solutions to be generated as part of a process of evaluating alternative technologies or policy interventions for risk-averse farmers.

More information on methods of risk analysis, including simple illustrations of most of the software packages mentioned here, is given in Hardaker, Huirne and Anderson (1997).

Summing up

Accounting for risk in the analysis of farming systems is much harder than pretending it doesn't exist. In the past, the difficulties have been compounded by confusion over just what risk is and how it can be measured. In the first part of this paper, an attempt has been made to resolve that difficulty. It seems that risk is best formalised as the whole distribution of outcomes.

Risk analysis in agriculture has stumbled in the past because of difficulties in assessing and categorising farmers' attitudes to risk. While no easy solutions to these problems are offered in this paper, it is argued that risk aversion may not be as important for some choices as commonly believed. Moreover, as described above, there are some rough and ready ways to estimate the relevant range of risk aversion for some target group. Methods of stochastic efficiency analysis then allow at least something to be said about better and worse solutions.

Some risk analyses that have been based on brave assumptions about the degree of risk aversion have overlooked some of the complexity in making the move from utility of wealth to utility of gains and losses or the utility of income. Moreover, very few such analyses have recognised that risk aversion for permanent income is likely to be much more important than is risk aversion for transitory income.

Risk analysis has also been avoided in the past because so many would-be analysts were afraid to tackle the evaluation of risky choices when too few hard data were available to work out the required probability distributions 'objectively'. Too many of those who braved the waters of risk analysis left untold or under-emphasised the dubious relevance to the problem at hand of the data they used to represent uncertainty. It seems that the task of finding better ways to deduce the probability distributions that describe the risks that farmers face has been relatively neglected by agricultural economists. A part of this paper is therefore devoted to discussing subjective probabilities and to developing the elements of a code of practice for obtaining more refined probability estimates.

Finally, risk analysis has been limited till just a few years ago because the 'number crunching' task was too hard. Often, doing even quite simple stochastic analyses required the development of special-purpose computer programs. Those days are practically gone with the evolution of powerful and in some cases user-friendly software for risk analysis that can be implemented on PCs. In the last part of this paper, some information about the computing options now available is given.

Risk analysis is, and will remain, the art of the possible. But successful artistry needs to be founded on a good knowledge of principles and technique. At least a few of these matters are addressed above. The views and ideas given are offered as a small contribution to the eventual production of better pictures of the risky reality that farmers face.

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