CHANCE AND CHOICE WEST OF THE DARLING

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Twenty-one pastoralists in the West Darling region of New South Wales were interviewed to gain an understanding of the attitudes of managers in this high-risk pastoral area to uncertain prospects. It was found that pastoralists had no difficulty in specifying subjective probabilities but in modifying probabilistic information they were conservative relative to the 'correct' revision implied by Bayes' Theorem. All the surveyed pastoralists were non-indifferent to risk, as evidenced by their non-linear utility functions for gains and losses.

Introduction

Mounting evidence attests to the fact that farmers generally have a non-neutral attitude to risk [17]. The importance of this fact in guiding policy formulation generally has been emphasized in Dillon's recent review of utility theory [5] where note is taken of some specific implications for research [16] and extension [18].

The central theme of utility analysis or preference theory [14] runs as follows. If individuals make decisions in accord with a few specific but reasonable rules, then they should attempt to maximize expected utility in all their risky decision making. Preference theory is thus primarily a normative theory designed to aid people through the complexities of making risky decisions. Operationally it consists of separating explicitly the key components of risky decision problems—on the one hand degrees of belief in the occurrence of events (i.e., subjective probabilities), and on the other hand degrees of preference for risky outcomes (i.e., utilities).

The survey reported here was designed to assess farmers' degrees of belief and degrees of preference and thus to add generally to the stock of documented information on subjective probabilities and utility functions. The farmers chosen for interview during late 1969 were twenty-one pastoralists operating west of the Darling River in New South Wales. Selection was non-random.[1] All these managers nominated weather as the main source of uncertainty in the area. The location of the survey in this low-rainfall (about ten inches per annum with standard deviation of about four inches) climatically risky area was deliberate as the breed of farm operators who opt for such risky production has seemingly not been studied in this manner previously.

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[1] Names of pastoralists were obtained from a University of New South Wales research student resident in Broken Hill. Pastoralists were contacted by telephone prior to interview and all excepting one contact was successful in securing a complete interview. Sixteen properties were in the Broken Hill district and five were in the Tibooburra district.

Subjective Probabilities

For present purposes, a subjective probability is defined as a number in the range zero to one which describes a person's assessment of the likelihood of a future possibly non-repetitive event. This number, called the subjective probability of that event, is personal and conforms to all the rules of probability [24]. Subjective probabilities thus provide the means by which decisions under non-certainty become decisions under risk. If the decision maker is responsible for his decisions, his strengths of conviction about future events are appropriate rather than those of someone else. These probabilities provide the means by which intuitive knowledge and additional subjective information can readily and formally be incorporated in the decision framework. In real-world decisions, non-repeatability is the norm rather than an exception so that 'objective' probabilities about relevant future events generally do not exist. The major difficulty voiced by critics of subjective probabilities is the loss of 'scientific objectivity' implicit in the personal view of probability. However, it is clear that personal differences do play a significant role in decision making. Any useful decision-making framework should not rule out the possibility that disagreement is reasonable even when the same information is available to two reasonable persons. However, it is assumed that assessed probabilities always conform to the rules of mathematical probability. This is the requirement of internal consistency or coherence.

Considerable recent attention has been given to subjective probability estimation by Becker and McClintock [1], Edwards [8], Raiffa [21], Schlaifer [25], Tversky [28], Winkler [29], and others. Some report measures of subjective probability elicited in sophisticated laboratory experiments, whereas others describe various subjective distributions related to risky decisions. Apart from an early attempt by Williams [30] and a recent study by Carlson [3], specific studies of subjective probabilities in an agricultural economics context do not appear to have been reported.

Subjective probability estimates were elicited in this survey with the purpose of studying whether pastoralists could assess their degrees of belief for future states of nature of several relevant variables. The procedure used was as follows. For each random variable, the respondent's minimum and maximum values were first established. This range was separated into several equal intervals and the respondent was then asked to distribute a total of 25 counters over the different intervals in accordance with his degree of belief of the occurrence of each interval. In such a way discrete probability distributions were obtained for each of three future variables, namely: (a) wool price in cents per lb. in 1971, (b) lamb marking percentage relative to ewes joined in 1971, and (c) annual rainfall in inches in 1971. The distributions obtained were quite variable with different levels of mean, variance, skewness and kurtosis characterizing the degrees of belief of different respondents.

Respondents accepted the system quite readily and placed the counters without difficulty. Some initially left gaps in a distribution but when asked to explain this they admitted that there was 'some chance' for that interval and they reshuffled the counters in such a manner that there were no zero frequencies in the range. No time limit was placed on finishing and a subject could dwell on a problem as long as he wished until he firmly believed the distribution adequately represented his degrees of belief.

By way of example, the distribution of wool prices in 1971 for Respondent (5) was:

Price Interval (c/lb.):	27–29	30–32	33–35	36–38	39–41
Counters :	5/25	12/25	6/25	1/25	1/25

In a similar way, subjective distributions were obtained for rainfall (1971) and lamb marking percentage (1971). Intervals were specified on the premise that only integer values of wool prices (and lamb marking percentage and rainfall) were possible. This is obviously not true but respondents apparently thought in these terms.

Generally there are two problems that arise when measuring subjective probability. The first is coherency with the rules and axioms of probability. This problem was immediately overcome by requiring subjects to place all counters on the sheet presented. Thus total probability was always equal to one. The second problem is called psychic bias. This refers to the fact that some people have probability preferences as has been shown by Cohen [4] and Edwards [7]. Fellner [10], on the other hand, has argued that subjective probabilities are slanted or discounted in relation to the uncertainty with which they are formulated. It seems possible that psychic biases of various types and magnitudes were present in the subjective probability estimates. However, psychic bias can be regarded as a refinement that should not be regarded as importantly as the more pressing problem of obtaining some estimate of producers' subjective probabilities. It is more important to show that subjective probabilities are 'behind' decisions and that subjective probabilities can be associated explicitly with uncertain events.

We view the present exercise as a successful demonstration that decision makers in farming have a working familiarity with the concept of probability and that subjective probabilities can be readily elicited for at least some important random variables. The interview method used in obtaining these distributions was crude and imperfect but simple and apparently effective. It seems likely that the method of 'judgmental fractiles' (e.g. as expounded by Raiffa [21, pp. 161-168]) may be as simple to use in interviews and may give a better representation of subjective distributions. However, this alternative method is based on estimating cumulative probability functions which were judged as being relatively inconvenient for the present purpose.

In searching for formal ways of presenting these distributions concisely, several types of distributions were discarded because of the restrictive assumptions implied in their use. The Pearson curves [9] were adopted as an appropriate system to represent the subjective probability distributions. This system of density functions, developed by Karl Pearson in a series of papers commencing in 1895, provides a wide variety of forms. It found a central role in statistical theory because it contains as special cases the normal, the Chi square, Cauchy, rectangular and Student 't' distributions.

Pearson's family of distributions has the disadvantage that, as the relevant sampling theory has not yet been discovered, hypothesis testing is not possible. This presents no problems from the point of view of this study. Subjective probability distributions are strictly personal, so comparisons between subjects lack meaning and the interest here is only in reporting a concise and formal way of representing subjective distributions. Given this, there is more interest in the qualitative characteristics than the quantitative ones.

Probability distributions are conveniently described by the first four sample moments m_1, m_2, m_3 and m_4 and a measure of relative skewness, $\alpha_3 = m_3/m_2^{3/2}$ and a measure of relative kurtosis, $\alpha_4 = m_4/m_2^2$. For the density function of the normal distribution, $\alpha_3 = 0$ and $\alpha_4 = 3$. For other density functions a positive value of α_3 connotes positive skewness, that is, a relatively long tail to the right and a mode less than the mean. A negative value of α_3 indicates negative skewness with mean below the mode. A value of $\alpha_4 > 3$ indicates a density function more peaked and with more extended tails than the normal. An $\alpha_4 < 3$ indicates a flatter top and with more abruptly diminishing tails than the normal [9].

The reader will not be surprised to learn that probability distributions differed considerably between individual pastoralists—indeed this is the *raison d'etre* for subjective probability. By way of example, descriptive statistics for the distributions of an arbitrarily chosen sub-set of respondents are reported in Table 1. Full details of all distributions elicited are available in Francisco [12].

TABLE 1

Moment Descriptions of Some Subjective Probability Distributions

Random Variable	Respondent number	Mean m_1	SD $m_2^{1/2}$	Skewness α_3	Kurtosis α_4
1971 Wool price (c/lb.)	5	31·7	2·8	0·9	4·0
	6	31·4	1·8	0·1	2·1
	7	35·0	2·0	0·1	2·8
	8	35·3	1·1	—0·4	2·2
	9	59·4	3·4	—0·9	2·6
	10	32·1	1·9	0·4	1·1
	Average of 21 respondents	38·9	2·3	0·16	2·4
1971 Lamb marking (per cent)	5	90·8	3·0	0·4	2·5
	6	82·1	6·9	0·2	1·9
	7	82·3	9·4	—0·0	2·2
	8	93·3	6·1	—0·6	0·2
	9	86·5	2·7	—1·1	2·8
	10	72·5	5·6	—2·6	8·3
	Average of 20 respondents	76·2	7·5	—0·28	3·0
1971 Rainfall (inches)	5	8·8	3·5	0·2	2·6
	6	7·2	2·8	—0·5	2·5
	7	6·5	2·8	—0·0	2·3
	8	8·0	1·8	0·0	2·5
	9	10·1	3·0	0·3	2·4
	10	8·0	1·8	0·0	2·5
	Average of 21 respondents	7·5	2·6	0·02	3·1

The form of further analysis of such subjective distributions would depend on the use to which they were to be put. They might, for instance, be used directly in analysis of some risky decision problems. For other decision problems the particular discrete intervals initially obtained may be inappropriate and the distributions would need to be smoothed. This could be done in many ways with perhaps the simplest method being the hand-smoothing of cumulative probability curves [25]. Another procedure that is fairly simple if a computer program is available (e.g. [20]) is to fit the Pearson frequency curves [9]. This was done in the present instance and was fairly successful in about 60 per cent of the attempts. The Pearson system only seemed to work well when the elicited histogram was unimodal and fairly symmetric. As such we do not recommend it as a useful smoothing device.

Revision of Probabilities

In the modern approach to risky decision analysis, subjective probabilities constitute a foremost facet of formulating decision problems. Another important aspect is the revision of (prior) probabilities attached to a random variable in the light of new probabilistic sample information (which may also be subjective). This revision process can be simply and quite mechanically conducted by using Bayes' Theorem.

In the Bayesian view, Bayes' Theorem expresses 'the essence of inductive reasoning of the process of learning from experience' (Roberts [22, p. 137]). The Bayesian approach incorporates the decision maker's prior probability distribution (reflecting his prior knowledge) to form a posterior distribution on which decisions can be based. The impact of prior probabilities differs greatly from one problem to another. If observations have low variance relative to the prior distribution, the form and properties of the prior distribution have relatively minor influence on the posterior distribution. From a practical point of view any vagueness of subjective opinion diminishes sharply as soon as a few data become available. Two people with widely divergent prior opinions would probably reach arbitrarily close agreement about future observations by observing sufficient common data.

For the present purposes consider a simple problem of two states and define H_1 as Hypothesis One, H_2 as Hypothesis Two where $P(H_2) = 1 - P(H_1)$ and D as evidence. The conventional form of Bayes' Theorem is then

$$P(H_i|D) = \frac{P(H_i)\ P(D|H_i)}{P(D)}.$$

The ratio $P(H_1)/P(H_2)$ defines the prior odds in favour of Hypothesis One. The conditional probabilities (likelihoods) of D given H_1 and H_2 are $P(D|H_1)$ and $P(D|H_2)$, and the ratio $P(D|H_1)/P(D|H_2)$ is called the likelihood ratio. The posterior probabilities of H_1 and H_2 given D are, respectively, $P(H_1|D)$ and $P(H_2|D)$ so that $P(H_1|D)/P(H_2|D)$ is the posterior odds ratio for Hypothesis One. The odds ratio form of Bayes' Theorem [26] relates prior posterior probabilities via the likelihoods as: posterior odds ratio equals prior odds ratio by likelihood ratio, i.e.

$$\frac{P(H_1|D)}{P(H_2|D)} = \frac{P(H_1)\ P(D|H_1)}{P(H_2)\ P(D|H_2)},$$

and taking logarithms this can be expressed as, log posterior odds equals log prior odds plus log likelihood.

This last expression provides a means of assessing how accurately, relative to Bayes' Theorem, people revise probabilities. The measure defined by Phillips and Edwards [19] in their study of this topic is

$$\text{Accuracy ratio} = \frac{\text{Observed log likelihood ratio}}{\text{Bayesian log likelihood ratio}},$$

where the numerator is the difference between observed log posterior odds and observed log prior odds and the denominator comes from the corresponding Bayes' Theorem calculations.

This accuracy ratio will equal one when subjective revision is identical with Bayesian revision and will take values smaller than one when the assessor revises probabilities conservatively. Typically, people are conservative information processors in the sense that they do not extract from information as much reduction of uncertainty as the information could justify. This is what has been called by Phillips and Edwards [19] the 'conservatism effect'. Several laboratory experiments have compared 'intuitive' revision of subjective probabilities with correct revision as calculated by means of Bayes' Theorem and the typical finding is that subjects are conservative.

Better use of available information is a potentially important issue in assisting farmers and pastoralists to make better decisions. Here, however, we consider how well our respondents handled additional information. The framework used was to pose a hypothetical situation in which the respondent was faced with two identical bags with marbles of two colours. The bags were explained to have the following compositions.

	Red	Black
Bag 1	7	3
Bag 2	3	7

Bag 1 was defined as 'predominantly red' and bag 2 as 'predominantly black'. This presentation closely follows the 'Ellsberg urn' problem reported by Smith [27], and by Sanders and Linden [23] in a different presentation based on light flashes.

Independent experiments of sampling with replacement for various combinations of coloured draws were put to respondents and their revised probabilities on which bag was which were recorded.[2] In all cases the prior probabilities on which was the 'red' and the 'black' bag were equal to 0·5. Only the results for one sequence of experiments are discussed since they are typical of others obtained. The sequences to be

[2] 'If I choose one of the bags and show it to you, what chance do you think you would have of correctly identifying the bag? You are not allowed to look inside. Both bags are the same.'

Once he assessed this probability (and all respondents assessed it as 0·5) the second question put was: 'Suppose I drew one marble at random from the bag. If I drew a *red* marble, what chance do you think there is that the bag is predominantly red or predominantly black?' The third question was: 'We start again with a full bag. Now suppose that you were able to draw a marble at random from the bag, see its colour, put it back, shake the bag and draw another marble. You would then know the colour of two marbles at random from the bag. If both marbles were red, what chance do you think there is that the bag is predominantly red or predominantly black?'

The questions continued in this fashion for varying colours of draws and increasing the number of draws to three. Each question was independent of the others. That is, knowledge of the hypothetical bag was increased because of the increased number of observed marbles at each drawing and not because of information obtained from previous questions.

considered had the outcomes, 1R, 2R, 3R where, for example, 2R denotes two red marbles drawn with replacement. The Bayes' Theorem posterior probabilities are easily calculated for these outcomes (e.g. [21], p. 21) and these were used in conjunction with the observed posterior probabilities to calculate the previously defined accuracy ratios.

Some representative examples of the results obtained are reported in Table 2 along with the mean accuracy ratios for the 20 respondents who participated in the exercise. The ratios illustrate a diversity of revisions of probabilities and it is not too surprising to observe that no one was exactly or even very closely in accord with Bayes' Theorem. It should be noted that, on average, the respondents tended to revise probabilities in a more Bayesian manner the greater was the sample information (more red draws) available. However, all but two (10 per cent) of the respondents can be broadly described as conservative users of probabilistic information and this accords with the findings of psychological research [19]. Thus it appears that arid zone pastoralists are generally similar, in the manner they process such additional information, to the people analogously tested by experimental psychologists—usually students or soldiers.

TABLE 2

Accuracy Ratios for Probability Revision in the Hypothetical Situation

Representative respondent number	Accuracy Ratio[a]			Number of broadly similar responses
	1R	2R	3R	
9	0	0	0	2
7	0	0·84	0·33	5
21	0	0·66	0·85	5
11	0·49	0·60	0·85	5
6	1·0	0·66	0·34	2
1	1·3	1·0	0·54	1
Average of 20 respondents	0·29	0·56	0·54	

[a] Ratio of unity indicates perfect Bayesian revision; ratio of less than unity indicates conservative revision.

Empirical Utility Functions

The concept of the utility (or preference) function is at the heart of the modern treatment of decision making under uncertainty. Utility theory is the subject of several excellent recent textbooks (e.g. [2], [13], [21] and [25]) and we feel that further expository review here would serve no good purpose. Suffice to say that the theory postulates the existence of utility functions unique to individuals, such that each individual will make the best decisions consistent with his beliefs and preferences if he attempts to maximize expected utility.

Since most business and farming decisions involve outcomes that can be expressed in money terms, the argument of utility functions of most practical importance is money. The present empirical work thus relates to the utility for instantaneous monetary gains and losses—thereby conveniently avoiding the additional complexities of time preference [15].

Our survey was addressed to the empirical question of the shape of pastoralists' utility functions. This question is of importance because, whereas utility theory takes the view that virtually any monotonically increasing function can be an acceptable utility function, much conventional economic analysis assumes (often implicitly) that decision makers' utility functions are linear [6]. A linear utility function implies, amongst many things, that its owner should maximize expected monetary value in his risky decision making.

Many methods have been proposed and used for estimating utility functions [11]. We seized on a method that is simple to use and apparently quite effective. This technique is known by various names including the Modified von Neumann-Morgenstern Method [17], and the Probabilistic Mid-point Method [11]. It consists of the decision maker finding a sum of money (certainty equivalent) for which he is indifferent to receiving that sum for certain and participating in a 50:50 gamble involving specified monetary payoffs. For instance, the first preference question in the survey was to ascertain the pastoralist's certainty equivalent, C, for a risky prospect involving possible payoffs of \$40,000 or \$—20,000 each with probability 0·5. Thus the utility of C is given by

$$U(\$C) = 0{\cdot}5U(\$40{,}000) + 0{\cdot}5U(\$-20{,}000).$$

Utility scales, like temperature scales, have no unique origin or units so that arbitrary values can be given to any two points on a utility function. When eight-inch graph paper is used as in the survey, a convenient scale here is $U(-20{,}000) = 0$, and $U(40{,}000) = 8$, so that $U(C) = 4$.

The method proceeds by finding certainty equivalents that successively divide the utility scale into a number of equal-utility segments. Eight segments (nine points) were found to be adequate for sketching a smooth free-hand curve through the co-ordinates determined. A number of 'check' questions [17] are included to ensure that the estimated function is a consistent representation of the individual's preferences.

As was to be anticipated from the experience of Officer and Halter [17], respondents found it fairly easy to answer the utility questions and consequently 21 smooth utility curves were readily obtained. The most important finding in this exercise was that none of the utility functions was linear over this \$60,000 range of payoffs, which we believe encompasses the payoffs involved in most operational decisions on West Darling properties.

A few representative utility curves are reported in Figure 1 to demonstrate the diversity of shapes encountered. Most (19/21) curves are S-shaped indicating that these pastoralists tend to be risk-averse concerning relatively large gains and risk-preferring where relatively large losses are involved.

The curves for No. 9 and No. 13 represented by two of the unbroken lines in Figure 1 stand apart from the others. Respondent 9 exhibited increasing marginal utility for money (risk preference) over the entire range tested. The curve for Respondent 13 has two inflexion points in this range of monetary payoffs and indicates that he has only a restricted range of (positive) payoffs for which he is risk averse.

The large group of S-shaped curves is summarized in Figure 1 by four representative curves for Respondents 18, 5, 11 and 4 designated shape Types 1, 2, 3 and 4 respectively. The other curves in each of these type

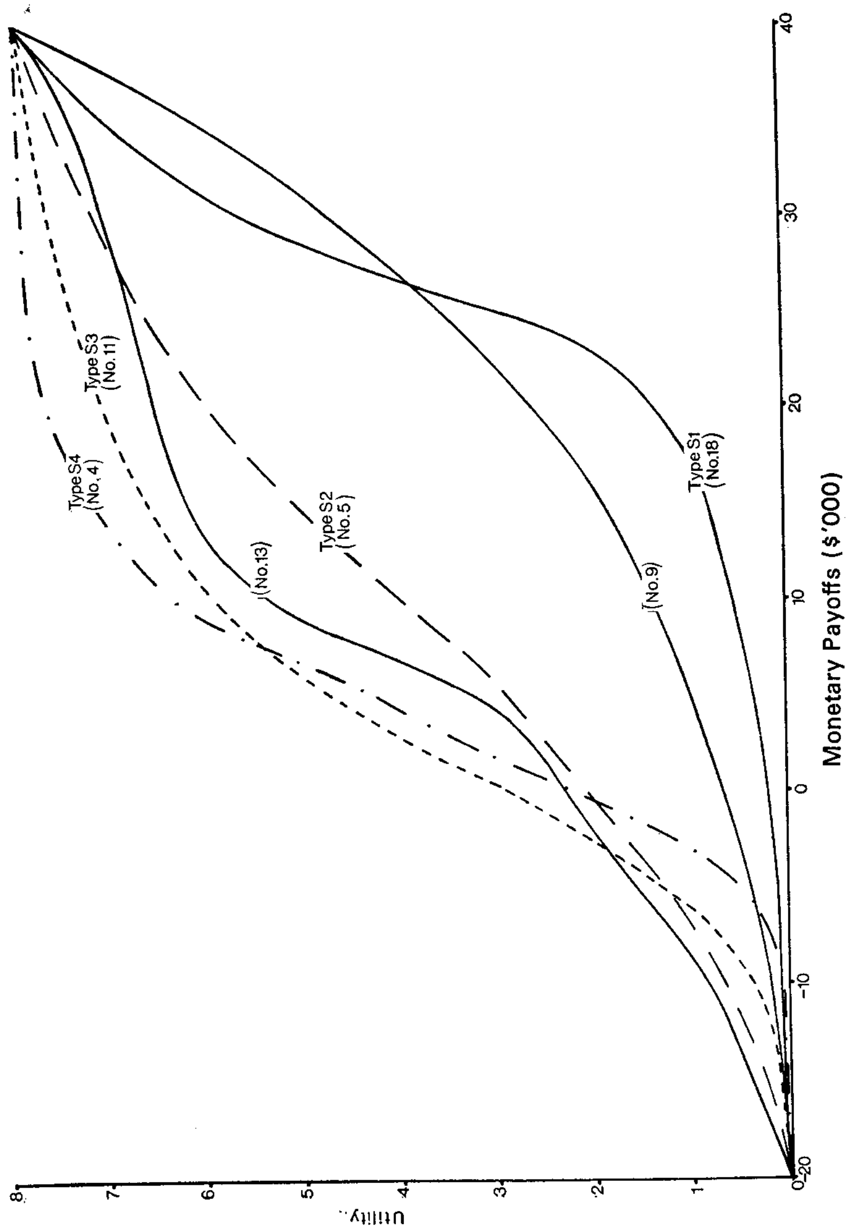

FIG. 1—Six pastoralists' utility functions for gains and losses.

TABLE 3

A Simple Classification of the S-Shaped Utility Curves

Type Shape from Figure 1							
Type S1		Type S2		Type S3		Type S4	
Respondent number	Inflexion point	Respondent number	Inflexion point	Respondent number	Inflexion point	Respondent number	Inflexion point
	$'000		$'000		$'000		$'000
19	25	5	12	16	−4	2	4
18	26	7	14	11	1	4	6
17	30	8	14	3	3	21	7
10	38			12	4	6	9
						15	9
						14	11
						20	11
						1	16

groups have a rather similar shape to the representative member but differ at the money level of the inflexion points. The approximate inflexion points are listed in Table 3. For monetary payoffs less than the inflexion point each respondent is risk preferring over the range tested. Thus the Type S1 respondents are risk preferers over most of the range. At the other extreme, Type S3 and some of Type S4 respondents are risk averse over most of the tested range of positive monetary gains. The remaining respondents with S-shaped curves are in an intermediate position with respect to risk preference and aversion.

Considering the riskiness of arid-zone wool production, it is perhaps not surprising to find the observed extent of risk preference in these pastoralists' utility functions. The important result, of course, is the implications that the measured risk preference and risk aversion have for resource use. For instance, the non-linear utility functions imply that there is no unique 'optimal' stocking rate but that the best rate for each pastoralist must take into account his individual attitude to risk [16]. An analysis [12] of a West Darling stocking rate problem using these utility functions indicated a diversity of utility-maximizing stock rates ranging from about 15 to 25 acres per sheep with most differing substantially from the rates that maximize expected monetary value. Individuality of preference similarly pervades all farmers' risky decision making with consequent impact for advisory services directed at assisting farmers in their decisions [18].

Conclusions

Our survey of West Darling pastoralists focused attention on their degrees of belief (subjective probabilities) and degrees of preference for risky monetaary payoffs (utilities). We found that subjective probability distributions can be readily elicited from respondents, thereby emphasizing their fair (perhaps intuitive) understanding of the probability concept. Elicited distributions can be smoothed and summarized in many ways, but our experience suggests that fitting the Pearson frequency curves is not a very worthwhile practical endeavour.

The manner in which pastoralists revise subjective probabilities in the light of new probabilistic information was investigated in a hypothetical framework. This investigation revealed that pastoralists, like most other groups that have been examined, tend to be conservative in revising probabilities—that is, they do not extract as much information from new sample information as they should. Thus there is ample scope for using Bayes' Theorem explicitly in assisting decision makers to make appropriate use of new probabilistic information.

Finally, it was found that all interviewed pastoralists had non-linear utility functions for gains and losses. This finding of a non-indifferent attitude to risky outcomes is not surprising but it seems to emphasize the relevance and importance of attempting to take account of preference in aiding primary producers to make good consistent decisions.

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