The Elicitation of Subjective Probabilities with Applications in Agricultural Economics

Patricia E. Norris and Randall A. Kramer*

Probability judgements are important components of decision making under uncertainty. In particular, economic decisions can be aided by assuring more accurate assessment of probabilities and more realistic modelling of economic problems through the inclusion of subjective probabilities. The purpose of this paper is to describe the techniques which can be used to elicit subjective probabilities and the ways in which these techniques can be incorporated into agricultural economics research. The review draws from the statistics, psychology, management, operations research, meteorology and economics literature.

Introduction

Studies on the elicitation of subjective probabilities and their use in decision making have been conducted by researchers in many fields. Psychologists, meteorologists, statisticians, investment analysts, management scientists and economists alike have recognized the importance of considering decision makers' subjective probabilities in situations where uncertainties pervade. There are two principal reasons for the widespread interest in subjective probability. First, it is clear that we live in a probabilistic and unpredictable world. Thus, probability judgements often must guide our behaviour in everyday life. Second, subjective probability is a fundamental element of theories of decision making under uncertainty, and a working knowledge of how people make probability judgements is essential for the application of such theories.

A greater familiarity with the elicitation and use of subjective probabilities would be valuable for both researchers and extension personnel in agricultural economics. The pervasive uncertainties associated with the production and consumption of agricultural commodities present a fertile opportunity for incorporating subjective probability considerations into economic analyses. In addition, economic decisions in these areas can be aided by assuring more accurate assessment of probabilities and more realistic modelling of decisions through the inclusion of subjective probabilities.

The purpose of this article is to review the literature on elicitation of subjective probabilities. The primary focus of the review is the description of various methods which have been used for assessing probabilities. The paper begins with a brief discussion of subjective probability distributions and their properties, after which a number of elicitation techniques are described. Next, guidelines for evaluating assessments and assessors are addressed. Then, a review is provided of research by agricultural economists who have elicited and used subjective probabilities. Finally, considerations for choosing an elicitation technique and for additional applications of subjective probability elicitation in agricultural economics research are presented.

Defining Subjective Probability

Subjective, or personal, probabilities have been defined as beliefs held by individuals which reflect their degree of uncertainty about some idea, event or proposition (Bessler 1984). The probability that a person attaches to a particular event measures his or her degree of belief that the event will occur (Hogarth 1975). The probability is subjective in that it expresses the feeling of an individual, and the individual's degree of belief regarding the occur-

* Assistant Professor, Department of Agricultural Economics, Oklahoma State University, and Associate Professor, Center for Resource and Environmental Policy Research, Duke University, respectively. This study was funded in part by a cooperative agreement between Virginia Polytechnic Institute and State University and the Extension Service and Federal Crop Insurance Corporation of the U.S. Department of Agriculture. The authors wish to thank David Bessler, S. SriRamaratnam, Oral Capps, Darrell Bosch, Brian Hardaker, James Pease, Odell Walker and anonymous journal reviewers for comments on earlier drafts of this report.

rence of a given event depends on the information available to him or her (de Finetti 1964). As a result, subjective probabilities may vary from person to person for the same event, if they have different backgrounds and information or if they interpret the same information differently (Stael von Holstein 1970).

Differing probability assessments across individuals is one distinction between subjective probabilities and "objective" probabilities or long run frequencies. The primary difference between the two, though, is that the long run frequency interpretation of probability requires a long series of trials under identical conditions to determine probabilities with reasonable accuracy. Subjective probabilities, on the other hand, may describe situations which occur only once or even events which have never occurred.[1] The importance of subjective probabilities in decision making arises because so many practical decision problems involve uncertain quantities for which relevant long run frequencies are not available.

Subjective probability assessments may take one of two forms. The first is a prediction of the likelihood of a particular event's occurrence and is referred to as a point estimate. However, when there is a very large number of possible events or outcomes, the assessment of individual probabilities becomes very difficult. Then, a second approach, the assessment of an entire probability distribution, is more appropriate. A subjective probability distribution is a set of subjective beliefs defined over a number of mutually exclusive and exhaustive events. For example, an agricultural producer who makes a production decision based on the judgement that there is a 90 per cent probability that the price of corn will be \$2.65 at harvest has used a point estimate. However, it is more reasonable to expect that the price of corn will, in fact, fall somewhere between \$2.00 and \$3.50. Therefore, a probability distribution which assigns probabilities to all values within a range may be more realistic. As discussed below, such a distribution must satisfy certain conditions in order to accurately assess probability.

Conditions for Subjective Probability Distributions

The subjective interpretation of probability does not prescribe what opinions people should hold, but merely how they should be held (Hogarth 1975). Two primary conditions define the "how": coherence and compatibility. First, the coherence condition requires that the assessed probabilities be consistent with the axioms, rules and calculus of probability. Second, they should be compatible with the actual beliefs held by the assessor (Anderson *et al.* 1977).

The condition of coherence requires that the following axioms of probability be satisfied:

1. The probability of a given event is a number between 0 and 1 inclusive.

2. The sum of the probabilities of all possible events is equal to one.

3. If two events are mutually exclusive, then the probability that at least one of the two events will occur is the sum of the individual probabilities.[2]

The second condition, compatibility, requires that judgements are compatible with the assessor's true beliefs regarding the event under consideration. In addition, it is essential that the expressed subjective probabilities are consistent with all other beliefs held by the individual. Tversky and Kahneman (1975, p.160) suggested that the coherence condition is necessary but not sufficient and stressed the importance of the compatibility condition:

> The inherently subjective nature of probability has led many students to the belief that coherence, or internal consistency, is the only valid criterion by which judged probabilities should be evaluated. From the standpoint of the formal theory of subjective probability, any set of internally consistent probability judgements is as good as any other. This criterion is not entirely satisfactory because an internally consistent set of subjective probabilities can be incompatible with other beliefs held by the individual. For judged probabilities to be considered

[1] Winkler (1972) has pointed out that the subjective interpretation of probability applies whether or not the situation is repetitive.

[2] Wallsten and Budescu (1983) argue that it is not necessary for elicited probabilities to satisfy the axioms of additive probability theory in order to be valid representations of probabilistic beliefs.

> adequate, or rational, internal consistency is not enough. The judgements must be compatible with the entire web of beliefs held by the individual.

Keeping assessors "honest" poses one of the more challenging problems in the elicitation of subjective probabilities and is a problem which has received attention from agricultural economists.

Eliciting Subjective Probabilities

Elicitation te chniques can be divided into two basic groups: direct and indirect methods. Direct techniques involve the direct questioning of assessors regarding their perceptions of the probability of an event or outcome. The questions asked require numbers as answers, in the form of either outcomes or probabilities. Alternatively, with indirect techniques, probabilities are inferred from preferences or choices between possible bets, decisions, or alternatives (Spetzler and Stael von Holstein 1975; Hampton *et al.* 1973). The two approaches can be used for either point estimation (estimation of the probability of a single event) or assessment of a probability distribution (the probabilities of a whole range of possible outcomes).

As noted previously, it is more appropriate to assess the entire subjective probability distribution when the number of possible outcomes is very large. Even if it is possible to assess individual probabilities for a large number of discrete events, it is unlikely that the individual probabilities would sum to one. In addition, if the probability assigned to one event were compared to the probability assigned to a different event, the individual assessments might seem unreasonable relative to one another (Schlaifer 1969). Because of these difficulties, and because most economic decision problems involve a range of possible outcomes, this review concentrates on research which has elicited entire probability distributions.

Direct Approaches

Probability distributions can be assessed either in the form of a probability density function (PDF) or a cumulative distribution function (CDF). Direct techniques are used to assess directly the points on the PDF or CDF. In general, with this approach, the assessor must first decide how the individual probabilities are to be related. When estimating a PDF, probabilities are assessed for a few outcomes and a curve is fitted to those points which agrees with each individual decision as well as the perceived relationship among the individual probabilities (Schlaifer 1969). When estimating a CDF, the assessor chooses values (or outcomes) for a few specific probabilities. Again, these points are plotted and a curve is fitted which represents the assessor's perception of the total distribution and the relationship between the individual probabilities. In either case, values can be read from the curve to see whether they agree with the assessor's actual judgements.

PDFs have been assessed using direct techniques in many studies. In some cases, probabilities have been assigned to specific values or outcomes (Ludke *et al.* 1977; Seaver *et al.* 1978; Winkler 1967). For example, individuals were asked to assign probabilities to a series of specific values to reflect their perceived likelihood of occurence. In other studies, assessors have assigned probabilities to intervals (Lin 1973; Bessler 1980; Kabus 1976). With this approach, the range of all possible values or outcomes is divided into a number of intervals (usually of equal width). The assessor provides for each interval an estimate of the probability that the true value or outcome lies within the interval.

Researchers eliciting CDFs have depended primarily on the method of successive subdivisions or bisection (Carlson 1970; Ludke *et al.* 1977; Moskowitz and Bullers 1979; Stael von Holstein 1970). These methods determine the fractiles of the CDF by asking assessors to divide an interval into subintervals or fractiles such that an event is equally likely to occur in any subinterval. With the successive subdivision method, the assessor is asked to determine that value for which there is a 50 per cent chance that the true value will be above or below it (the median value). Similarly, the quartiles are determined by dividing the two subintervals into equally likely parts. If, for example, eight mutually exclusive and exhaustive intervals are identified, then the values of the endpoints of those intervals have cumulative probabilities from zero to one in steps of 0.125.

The relative advantages of PDF and CDF methods have been discussed widely. There is some theoretical support for the use of CDF methods, in that the bisecting elicitation technique requires only equally likely responses and should be cognitively easier for assessors to use than direct magnitude elicitation techniques (Chesley 1978). CDFs have also been favoured because the assessment of very small probabilities in the "tails" of a PDF may be difficult (Hampton *et al.* 1973). However, cumulative error may be introduced into a CDF if the initial fractile estimate, for example the median value, is inaccurate, since that error will increase cumulatively as additional fractiles are based on that first value (Ludke *et al.* 1977). Also, after the median is established, the method of bisection may be more difficult, since it requires that the assessor disregard half of the probability distribution (Huber 1974). In practice, researchers have found that assessors are more comfortable using PDF methods and that PDF methods gave better results (Winkler 1967; Chesley 1978; Ludke *et al.* 1977). Ludke *et al.* (1977) concluded that, in general, PDF methods performed better than the CDF methods, based on their measures of accuracy, reliability and acceptability (see discussion of these criteria below).

What the direct PDF and CDF methods have in common is that they are "distribution free." They do not assume anything about the functional form of the probability distribution (Stael von Holstein 1970). Several researchers have proposed the assumption of specific distributions to facilitate elicitation of probability distributions. For example, assuming a triangular distribution, the assessor specifies the upper and lower endpoints and the mode of the distribution, in other words the highest possible, the lowest possible and the most likely outcomes (Sonka and Patrick 1984; Hull 1976). With this information, moments of the distribution can be estimated. Other researchers have assumed a beta distribution for their elicitation exercises, requiring the assessor to specify the mode and the zero and 100th percentiles of the distribution (Malcolm *et al.* 1959). Because of the potential difficulties associated with determining the zero and 100th percentile endpoints of a particular distribution, modified approaches have been suggested to elicit the first and 99th or fifth and 95th percentiles and use modified formulas to calculate the moments of the distribution (Young 1983; Moder and Rodgers 1968; Moskowitz and Bullers 1979). However, while assessors will give parameters of specific distributions, such as the beta, their responses may not reflect an understanding of the underlying distribution (Spetzler and Stael von Holstein 1975). A further limitation of the approaches described above is that the probability distribution is estimated based on only three data points. Spetzler and Stael von Holstein (1975) conclude that the choice of special distributions is a modelling consideration and should not normally be made part of the elicitation process.

Indirect Approaches

Because some assessors may experience difficulties making direct assessments, alternative techniques have been proposed which determine assessors' subjective probabilities indirectly. In general, indirect methods assess probabilities from individuals' decisions in a choice situation. Indirect techniques are so called because the relationships between the techniques and the resulting probabilities are not always clear to the assessor (Winkler 1967). Nevertheless, in some cases, assessors have found the indirect techniques simpler to use (Winkler 1967; Chesley 1978).

Most of the indirect methods have been designed to explicitly estimate either PDFs or CDFs. However, in many cases, slight changes in the wording of questions or instructions to assessors may change a PDF method to one which elicits a CDF. In the discussion which follows, use of the indirect techniques to elicit PDFs or CDFs is noted. Also, the number of indirect measures which has been suggested is quite large, and in many cases researchers may have worked with variations of the same technique. Therefore, in the following discussion, similar techniques are combined under the most common name. The different techniques are summarized in Table 1.

Gamble Methods:
With the gamble technique, questions are asked in terms of betting odds, and subjective probabilities are inferred from the odds required to make the assessor indifferent between two offered bets. Probabilities are determined cumulatively for the range of possible outcomes. In his analysis of pesticide use, Carlson (1970) used gamble questions to elicit subjective probability distributions of

Table 1. Names Given to Indirect Techniques for Eliciting Subjective Probabilities

Name Used Here	Names in Literature	Reference
Gamble Methods	Gamble Method	Carlson (1970)
	Lottery Method	Chesley (1978)
	Bid Method	Chesley (1978)
Odds Methods	Odds Method	Chesley (1978)
		Seaver *et al.* (1978)
	Log and Log-log odds	Ludke *et al.* (1977)
	Relative Likelihood	Spetzler and Stael von Holstein (1975)
		Hull (1976)
	Partial Expectations	Gibbs *et al.* (1987)
	Interval Method	Spetzler and Stael von Holstein (1975)
Weighting Method	Conviction Weights	Young (1983)
		Nelson and Harris (1978)
Visual Response Methods	Visual Counter	Francisco and Anderson (1972)
		Grisley and Kellogg (1983)
	Probability Wheel	Spetzler and Stael von Holstein (1975)
	Equivalent Urn	Spetzler and Stael von Holstein (1975)
		Hampton *et al.* (1973)
	Bar and Marker	Spetzler and Stael von Holstein (1975)
Ranking Method	Ranking Method	Smith (1967)
		Hull (1976)
		Ludke *et al.* (1977)
		Hampton *et al.* (1973)
Smoothing Method	Smoothing Historical Data	Hampton *et al.* (1973)
		Anderson (1973)
		Schlaifer (1969)

crop disease loss as a check for the PDFs and CDFs elicited with direct methods. Variations of the gamble technique were used by Chesley (1978) to elicit distributions related to the supply of a production input. Cumulative functions were estimated using what the author called bid and lottery methods. The bid method asked for a maximum bid the assessor would be willing to make for a one dollar payoff if the actual value in question were less than or equal to a specified value. The lottery method asked for the number of lottery tickets out of one hundred the assessor would require to be indifferent between the lottery and a decision situation where the payoff would occur if the actual value were less than or equal to the specified level.

Although assessors may find gamble methods simpler conceptually than direct approaches (Chesley 1978), the expense of offering payoffs to bets or gambles which are sufficiently realistic or attractive to encourage serious participation may be prohibitive (Savage 1971). Also, the gamble methods have been criticized because of their use of gambling terminology and because assessors' responses may be influenced by their attitudes toward risk in a "gambling" situation (Hampton *et al.* 1973). Two assessors who have similar subjective probability distributions but a different willingness to take risks may give widely different responses to hypothetical gambling questions.

Stael von Holstein and Matheson (1979) have suggested an elicitation method which may avoid the problems associated with the typical gamble or bet methods. Assessors are asked to decide whether they would prefer to bet a fixed sum of money on the outcome of a spin of an adjustable probability wheel (see the Visual Response Methods discussed below) or on the outcome of a particular event in question. Risk attitudes are circumvented because the same monetary value and the same subjective probability appear in both bets, thereby equating risks. While recognizing the advantages of this method, Wallsten and Budescu (1983) have pointed out an additional potential problem. Namely, probabilities on a wheel are obvious and precise, whereas those associated with the uncertain events are more or less vague, depending on the events and on the assessors.

Odds Methods:

Several researchers have found that, when estimating probabilities directly, assessors tend to overestimate small probabilities and underestimate large ones (Winkler 1967; Schaefer and Borcherding 1973). The odds method has been proposed to remedy this problem. Using this technique, assessors assign odds to an event's occurrence. For example, Seaver *et al.* (1978) determined points on a CDF by asking for values such that certain odds existed, e.g. "What is the number of people such that your odds are 3:1 that the true population of Canada is less than that number?" They also asked the assessors to assign odds to particular values in order to elicit PDFs.

Some assessors may find it difficult to understand the concept of odds or to express their expectations in terms of odds. In that case, the method of relative likelihoods, which is a simplification of the odds method, may be used. With this approach, the assessor first determines the most likely outcome and then estimates the relative chances of other outcomes occurring (Hull 1976). In their use of this technique, Spetzler and Stael von Holstein (1975) asked individuals to assign relative likelihoods or odds to two well defined events. First the assessors were asked which was more likely to occur, then how many times more likely. For example, a first question might be: "Are next year's sales more likely to be above or below 5000 units?" The next question is: "How many times more likely?" The researchers limited their use of this PDF technique to uncertain quantities that had only a few possible outcomes. A variation of this technique, referred to as the partial expectations method, was used by Gibbs *et al.* (1987) to elicit distributions for wheat yields from Australian farmers. Questions similar to those of Spetzler and Stael von Holstein were asked, but the researchers asked for responses stated as probabilities.

In another study, researchers used intervals to determine the likelihood of specific population characteristics and to estimate PDFs (Ludke *et al.* 1977)[3]. First, assessors were asked questions similar to: "How likely is it that an American male, age 18-79, will have a systolic blood pressure reading in one of the following ten intervals?" Then, to make answering simpler, the assessors were instructed to rank the ten intervals according to how many males they thought were contained in each. Finally, for each interval they estimated how many more males were in that interval compared to the number in the interval ranked directly beneath it.

Yet another simplification of the odds method is one which Spetzler and Stael von Holstein (1975) call the interval method. This indirect technique assesses the fractiles of a CDF in a manner similar to the direct fractile method. To use this procedure, an interval covering all possible outcomes is split into two parts. The assessor is asked which of the

[3] In the Ludke *et al.*(1977) study, odds scales were given in a log and log-log form, but researchers concluded that these scales resulted in distributions that were "too tight" (i.e. small variance).

two parts is considered most likely. The dividing point is changed to reduce the size of the part considered most likely, and the assessor is asked to choose between the two new parts. The position of the dividing point is adjusted until the assessor is indifferent between the two parts. These subintervals are assigned equal probabilities. Using this process, the median and then the quartiles are determined.

Weighting Method:
The weighting or conviction weights method requires assessors to assign weights to each outcome. One advantage of this method is that it assures that the assessed probabilities will sum to one. This approach also avoids the use of probability or odds terminology; such terminology may inhibit communication with assessors who have little or no statistical training. The conviction weights method asks individuals to assign a weight or score, for example a number between one and ten, indicating their strength of conviction that the outcome will occur in each of a set of intervals covering the range of possible outcomes (Young 1983; Nelson and Harris 1978). The scores are converted to probabilities by dividing each score by the sum of the assigned scores. Using this method, Pease (1986) presented individuals with price and yield ranges divided into a number of equal intervals and asked them to assign the most likely interval a weight or score of 100. Then, the assessors were asked to assign scores from zero to 100 to each interval representing how likely they perceived that interval relative to the most likely interval.

Visual Response Methods:
The visual response methods use visual tools to aid the assessor in assessing a PDF or CDF. One type of visual response method, the visual counter technique, resembles the conviction weights method discussed above. With this technique, the range of possible values or outcomes is divided into several equal intervals. Then, the assessor is asked to distribute a specific number of counters over the different intervals in accordance with his or her degree of belief of the occurrence of each interval. The probability assigned to each interval is calculated as the ratio of the number of counters assigned to the interval to the total available. Francisco and Anderson (1972) asked assessors to distribute 25 counters over intervals within specific ranges of values for wool price, lamb markings and rainfall. Grisley and Kellogg (1983) used this same technique, but they used 25 coins as the counters. As a motivational device, assessors were told they would receive the number of coins allocated to the interval which contained the actual outcome. In both studies, researchers found the visual counter method to be relatively easy to explain and administer, and assessors accepted the system readily.

Another visual response method is the probability wheel used by Spetzler and Stael von Holstein (1975). The wheel is a disk with two adjustable sectors, one blue and the other orange, and a fixed pointer in the center of the disk. The assessor is asked which of two events is considered the more likely - the uncertain event under consideration (for example, the event that next year's production will not exceed x units) or the event that, when the wheel is spun, the pointer ends up in the orange sector. The amount of orange in the wheel is then varied until the assessor finds the two events equally likely. The relative amount of orange is then assigned as the probability of the event. Similar tools used by Spetzler and Stael von Holstein (1975) are a bar with a movable marker and an urn with a number of balls of two colours. The location of the marker on the bar or the composition of the urn can be varied until it reflects the probability of the event in question.

Assessors have found it relatively easier to visualize the probabilities involved by using techniques such as these (Spetzler and Stael von Holstein 1975). Also, assessors' participation with manoeuvering these tools may increase their interest in the assessment process (Nelson and Harris 1978). It has been noted, however, that assessors may find it difficult to discriminate between sizes of small sectors on a wheel or bar. Therefore, it may be difficult to elicit small probabilities with these techniques (Spetzler and Stael von Holstein 1975).

Ranking Method:
Using the ranking technique, the assessor divides the range of all possible outcomes into a number of intervals and then ranks the intervals in order of ascending probability. In a second step, the differences between the probabilities of adjacently ranked intervals are ranked in ascending order (Hull 1976). Then, the rankings are translated into relative prob-

abilities (see Smith 1967), and the probabilities are plotted as a histogram which is smoothed into a frequency curve. It has been suggested that this procedure increases the replicability of the probability estimates because calculations are based on the rank order derived from the assessor's estimates rather than the estimates themselves (Smith 1967). Ludke *et al.* (1977) found that the ranking technique resulted in the most accurate and reliable estimates when compared with direct methods or odds methods. However, assessors found the procedure difficult to use. Hampton *et al.* (1973) have warned that the ranking of differences may be meaningless to the assessor and thus may tax his or her patience. Also, the method eliminates useful information by using the ordinal rank data rather than the estimated interval data (Ludke *et al.* 1977).

Smoothing Method:
This technique is based on the premise that historical data on frequencies are available to the assessor. Several researchers have argued that, when historical data are available, assessors should use such information in their assessments of probability distributions (Hampton *et al.* 1973; Anderson *et al.* 1977). First, the assessor uses historical relative frequencies as preliminary estimates. These estimates are revised to reflect the assessor's general beliefs about the shape of the distribution, while the set of revised estimates is kept as close to the original estimates as seems appropriate. The estimates are plotted and a curve is fitted (Schlaifer 1969). The approach is essentially the same whether the PDF or CDF is assessed; however, Hampton *et al.* (1973) suggest that a CDF is more appropriate if data are sparse. Anderson (1973) used this technique in an analysis of crop yield response to fertilizer. However, rather than ask farmers to smooth the data, Anderson did the smoothing before using the resulting CDFs to determine optimal fertilizer application levels.[4]

Additional Considerations - Understanding Probability Assessors

In addition to the technique itself, factors which will influence the elicitation process include 1) the level of assessor expertise, 2) the assessor's understanding of the problem, and 3) the type of feedback generated (Ludke *et al.* 1977). In general, the expertise of assessors is a function of two specific standards. First, the normative standard refers to the assessors' knowledge of probability concepts and the consistency of their assessments with the axioms of probability. Second, the substantive standard refers to the assessors' knowledge of the practical aspects of the problem at hand (Winkler and Murphy 1968).

Researchers have worked, in several cases, to train assessors prior to their experiments (Schaefer and Borcherding 1973; Branthwaite 1974; DuCharme and Donnell 1973). In most cases they have concentrated on instructing assessors with respect to probabilities and probability assessment. Winkler (1967) and Stael Von Holstein (1972) found that assessors who were more statistically knowledgeable were more accurate than assessors who were more knowledgeable about the phenomena in question. Instruction has not always improved the assessors' performances (Schaefer 1976) but in most cases has resulted in some improvement. Schaefer and Borcherding(1973) found that as assessors received feedback concerning normative criteria, their assessments became more realistic and the discrepancies between techniques were reduced. Nelson and Harris (1978) have suggested three particular characteristics of assessors which should be considered when designing an instructional package for training assessors: 1) their general level of education, 2) their current level of knowledge concerning probabilities, and 3) their communication and learning skills. These are characteristics which will vary widely across groups of assessors, areas of interest and levels of expertise.

Despite the normative or substantive expertise of an assessor, his or her assessment of a particular probability may not adequately describe underlying knowledge. Conscious or subconscious discrepancies between the assessor's responses and accurate descriptions of underlying knowledge are termed biases.[5] Sources of bias can be classified as motivational or cognitive. Motivational biases are either conscious or subconscious adjustments in the assessor's responses motivated by the per-

[4] The smoothing technique was based on Schlaifer's (1959, p. 104) rule: "If a sample of n observations is drawn from some distribution and arrayed in order of size, the pth observation is a reasonable estimate of the p/(n+1) fractile of the distribution."

[5] For a more detailed discussion of biases in probability elicitation, see Spetzler and Stael von Holstein (1975) and Hogarth (1987).

ceived system of personal rewards for various responses. Similarly, cognitive biases are adjustments, either conscious or subconscious, in the assessor's responses that are systematically introduced by the way the assessor intellectually processes perceptions.

Motivational biases may result from effects such as wishful thinking or the distortion of judgements by payoffs or penalties (Tversky and Kahneman 1975). For example, assessors might misrepresent their true beliefs if they wished to influence a decision that was to be based on their judgements. Similarly, assessors might expect a better evaluation of or reward for their assessments if they hedge away from their true judgements (Stael Von Holstein 1970). It is difficult to avoid these biases, but it is possible to develop an incentive scheme to encourage "honesty".

Some researchers have recommended the use of scoring rules to provide penalties or rewards as motivation for stated beliefs to correspond with true beliefs (Bessler 1984; de Finetti 1970). A scoring rule is used to calculate payoffs for different outcomes depending on the probability which the assessor assigns to that outcome. A proper scoring rule is one for which assessors maximize their expected scores if their stated beliefs equal their true beliefs. Typically, payoffs are calculated with a quadratic or logarithmic function, but possible payoffs are presented to assessors in graphical or tabular form.

Most applications of scoring rules have occurred in weather forecasting where the forecasters have the opportunity to go through many trials and get feedback on the accuracy of their forecasts in a short time (e.g. Murphy and Winkler 1984). Bessler (1977) and SriRamaratnam (1985) have reported success using scoring rules with farmers in eliciting subjective yield and price distributions. In their applications, no actual payoffs were made. Grisley and Kellogg (1983) reported the use of monetary payoffs with a scoring rule in the elicitation of farmers' subjective probabilities in Thailand.[6]

While these scoring rules may help reduce motivational bias, their use makes the elicitation of probabilities considerably more complex and time consuming. If researchers are obtaining price as well as yield distributions for several different crops, a scoring rule may overtax the assessor's patience. An additional problem is that if an individual is not risk neutral, a scoring rule may not eliminate the divergence between the elicited probabilities and the assessor's beliefs. As noted by Grisley and Kellogg (1985), maximization of expected utility is not equivalent to maximization of the expected score for a risk averse assessor.[7] Hampton *et al.* (1973, p.39) conclude that:

> The question of whether to use scoring rules or not becomes the problem of trading off the advantages of possibly obtaining more consistent estimates against the disadvantage of additional complexity and the introduction of further conceptual situations.

Cognitive biases may be introduced into probability assessments as a result of three particular heuristics, or mental operations: 1) representativeness, 2) availability, and 3) anchoring and adjustment (Tversky and Kahneman 1975). Representativeness may bias probability judgements if the probability of an event is evaluated according to the event's perceived representativeness of, or similarity to, a larger population of events (Kahneman and Tversky 1973). For example, a farmer in a developing country who has observed several new winter wheat varieties fail may underestimate the likelihood of success for a new rice variety. Because of the representativeness heuristic, he may ignore factors which should influence judgements of probability, such as differences in production techniques for wheat and rice.

Availability refers to the ease with which instances or occurrences can be brought to mind (Tversky and Kahneman 1975). As an example, a farmer might assess the probability of a major drought by recalling such occurrences in recent experience. Errors in assessments may occur, however, when they are based on availability. An event which is more easily remembered, whether through a recent experience or a more vivid experience, may be

[6] Their procedures were subsequently criticized because of the use of an "improper" scoring rule (Knight, Johnson and Finley 1985).

[7] See Bessler (1981) for a discussion of constructing an appropriate scoring rule when utility is nonlinear. Basically, the construction requires a composite function of the utility function and the old scoring rule.

judged to have a higher frequency than a less-remembered event of an equal frequency.

Anchoring and adjustment may bias probability assessments when people make estimates by starting from an initial value which is adjusted to yield the final value (Tversky and Kahneman 1975). Different starting points yield different estimates, which are biased towards the initial values. This phenomenon is called anchoring. Then, given the initial value, adjustments from that value are typically insufficient. For example, a U.S. corn producer who is focusing his farm planning on a target yield of 100 bushels per acre may anchor on that value during an elicitation exercise and fail to make sufficient adjustments from the anchored value. The result will be a subjective distribution which is too tight to reflect the true yield variability faced by the farmer.

These cognitive biases present the greatest problem for assessing probabilities which are compatible with the assessor's total set of beliefs. It is generally difficult for assessors to identify their heuristics and biases. Therefore, an important responsibility of the researcher is to discover what mental operations assessors might be using and then try to adapt the elicitation procedure to minimize biases (Spetzler and Stael Von Holstein 1975).

Evaluating Elicitation Techniques

The choice of an elicitation technique in a given situation is not obvious. It may be that a technique that works well in one situation will not work in another (Stael Von Holstein 1970). No method has had uniformly positive results (Ludke *et al.* 1977). Elicitation techniques have generally been evaluated in terms of three criteria: accuracy, reliability and acceptability.[8] The accuracy of an elicitation technique depends upon how well the subjective probability distribution elicited compares to some objective measure of the distribution. Two different types of accuracy have been defined. The first, internal validity or calibration, applies to *ex post* analysis of probabilities. An assessment is calibrated if, for those events assigned a probability p, the proportion that occurs is p (Wallsten and Budescu 1983). However, subjective probabilities are often elicited for unique or rare events for which the "true" probabilities are difficult, if not impossible, to obtain. Therefore, researchers have turned to a second method for establishing accuracy. This second method, external validity, compares the subjective probabilities to external measures which are defined *a priori* and independently of the assessor's estimates (Wallsten and Budescu 1983).

Ludke *et al.* (1977) assessed the accurancy of subjective distributions by comparing estimated values with actual probabilities using an analysis of variance technique. They found that the ranking method provided the most accurate estimates, when compared to the direct PDF, direct CDF and odds (log and log-log odds) methods. Moskowitz and Bullers (1979) used two measures to compare the accuracy of a direct CDF and a modified triangular distribution method. First, they considered "first moment bias," or how far the median (0.5 fractile) of the distribution deviates from the true value.[9] Next, they measured the "overconfidence bias" or the "second moment bias" as the dispersion of the distribution, where an overly tight distribution suggests that assessors express more knowledge about the uncertain quantity than they actually have. They concluded that there was little difference between the two methods in terms of first moment bias, but the triangular distribution method yielded less overconfidence bias in the probability estimates.

In general, reliability refers to the repetition, stability or consistency of elicited distributions (Wallsten and Budescu 1983). By one use of the term reliable, an elicitation technique is said to be reliable if an individual's estimates of the same distribution elicited at different times are consistent with each other (Ludke *et al.* 1977; Gibbs *et al.* 1987). Ludke *et al.* (1977) measured reliability using correlations between an assessor's probability estimates in a first session and estimates of the same probabilities in a

[8] See Wallsten and Budescu (1983), who use a slightly different terminology, for an extensive discussion of technique evaluation.

[9] In general, first moment bias refers to the deviation of the true value from some measure of central tendency. Normally the mean is the measure of central tendency used. However, Moskowitz and Bullers (1979) choose the median as their measure; their definition of first moment bias is "how far the median (0.5 fractile) or mode, considered the 'best' point estimate, deviates from the true value." For an asymmetric distribution, the median and mean will not be the same. Also, it is not clear why the authors chose to include the mode in their definition of first moment bias.

they found the ranking method to be significantly more reliable than the direct CDF and log-log odds methods. However, there was no significant difference between the ranking, log-odds and direct PDF methods.

Reliability has also been used to describe the consistency of probability distributions elicited by different techniques (Gibbs *et al.* 1987). Wallsten and Budescu (1983) refer to this definition of reliability as construct validity. A perfect correlation between estimates elicited with different techniques suggests that they represent a common subjective probability distribution. Beach and Phillips (1967) found a high correlation between probabilities elicited with a direct method and probabilities elicited with an indirect gamble technique.

Acceptability is defined with respect to the assessors' attitudes towards the techniques. In several studies, assessors were asked to rate the elicitation methods on the difficulty of learning the methods, the ease of using the methods, confidence in their estimates, and the length of time required to make the assessments (Ludke *et al.* 1977; Branthwaite 1974; Chesley 1978; Winkler 1967). Ludke *et al.* (1977) found that methods which required the estimation of probabilities were more acceptable to assessors than methods which required the estimation of odds. Winkler (1967) found that PDF methods were more intuitively appealing to assessors than CDF methods, and indirect techniques were rated by assessors as clearer than direct techniques.

An additional criterion which may be used to evaluate elicitation techniques is whether the subjective probabilities elicited can be used effectively, for example in decision analysis. For agricultural economics research, the use of subjective probabilities in decision models might be expected to improve the predictive ability of the models since the information underlying the assessor's decisions is more adequately represented. Several studies have examined the predictive ability of models which incorporate subjective probabilities; the results have been generally favourable (Lee *et al.* 1985; O'Mara 1971).

Subjective Probability Elicitation in Agricultural Economics Research: A Review

Agricultural economics research has contributed only a small portion of the extensive literature on the elicitation of subjective probabilities. Those agricultural economists who have worked with subjective probabilities used both direct and indirect elicitation techniques. In this section, applications are discussed by type of method used. Where possible, the techniques are evaluated according to their accuracy, reliability, acceptability, and predictive ability, based on the analyses conducted by the researchers.

Six of the studies reviewed made use of distribution free, direct techniques to elicit PDFs or CDFs. In Carlson's (1970) study of the disease control decisions faced by California peach growers, he elicited growers' subjective probability distributions for the level of crop loss due to peach brown-rot using two direct methods. For a sample of 76 growers, PDFs and CDFs were obtained by direct questioning. An indirect gamble technique was used as a checking device on some of the growers to ensure that the probabilities given were the probabilities that the growers were prepared to act upon. Assuming that the distributions elicited with the gamble technique best matched the farmers' beliefs, the PDFs were found to be the most reliable and were used in the analysis of disease control decisions. Using Bayes' Theorem, the subjective probabilities were combined with conditional probabilities estimated from a regression model. The resulting posterior probabilities were used, in an expected utility model, to determine the optimal pesticide use strategy.

O'Mara (1971) elicited subjective probability distributions for corn yields from a sample of central Mexico farmers. Using a series of five questions, the elicitation technique used determined the quartiles of a CDF. For example, the 0.5 quartile was assessed as "...the amount that yield will exceed two out of each four times." The probabilities were then incorporated into an expected utility analysis of the decision to adopt a new technology, and the theoretically optimal decisions were compared to the farmers' actual decisions.

In a study of farmers in California's Central Valley, Lin (1973) incorporated subjective probability distributions for prices and crop yields into his comparison of utility and profit maximization as objectives in agricultural production. PDFs were estimated with a direct method in which growers were asked to complete the following type of question for both yield and price variability: "Given your estimation of an average (expected) yield for cotton lint as 1500 pounds, what would be the chance in 20 years that your yields of cotton lint would fall between 1250 and 1350 pounds? Between 1350 and 1450 pounds?" etc. (Lin 1973, p.77). The probability distributions for prices and yields were used to estimate income variability, which was included in an expectations-variance (E-V) model of cropping decisions.

In a study of a sample of eastern Colorado farmers' crop insurance decisions, King (1982) elicited subjective probabilities for crop yields using a direct method to estimate CDFs. Farmers were asked questions of the type: "What is a very low yield for your farm, such that you would expect to exceed this yield in four out of five years?" A farmer's answer to this question, for example, determined the value for the 20th percentile. The resulting probability distributions were compared to historical yield frequencies, which were used as a measure of external validity. King concluded that in general the farmers were more optimistic about their yields than their historical yield distributions would warrant.

Knight (1984) used a direct PDF approach to elicit subjective probability distributions for short- and long-term hog prices. Distributions were elicited prior to and following extension outlook sessions. The pre- and post-programme distributions were incorporated into decision models and the results compared to determine the impact of the outlook programme on producers' decisions. Also, the post-programme subjective probability distributions were compared to distributions obtained through application of Bayes' Theorem to participants' pre-programme distributions. Results suggested that many, though not all, participants used the outlook forecast in a way that would have resulted in decisions consistent with their Bayes' strategies.

Kramer *et al.* (1986) used a direct PDF technique and a direct CDF technique to elicit subjective probability distributions for corn yields from a sample of Virginia corn growers. The PDF method presented farmers with yield ranges and asked for the number of years out of 20 that yields might be expected to fall into each range. The CDFs were obtained by the method of successive subdivisions. On average, the PDF method was given a slightly more favourable evaluation based on ease of understanding and the length of time taken to respond. The CDF method was a slight favourite with respect to ease of using and the level of confidence in the estimates. The farmers who preferred the CDF grew larger acreages of corn and tended to be relatively more educated. The means of the PDF and CDF responses were quite similar; however, the standard deviations differed widely. In addition, neither the PDFs nor the CDFs were found to correspond closely to historical yield distributions. The researchers also used an indirect technique, a variation on the visual counter method, and the direct PDF method to elicit yield distributions from wheat and barley growers. In general, the direct method was preferred. No significant conclusions could be drawn regarding the relative performance of the two methods.

Direct techniques which assume, *a priori*, the functional form of the distribution have also been used by a number of agricultural economics researchers. In particular, the triangular distribution has been used widely. Hanemann and Farnsworth (1981) used a modified triangular distribution method to elicit subjective probability distributions for cotton yields and insecticide expenditures associated with Integrated Pest Management (IPM) and conventional pest control strategies. PDFs were obtained from 44 cotton growers in California's San Joaquin Valley. The triangular distributions for yields and expenditures were compared to historical distributions; the subjective yield distributions closely matched the historical yield distributions. However, the growers' subjective distributions for expenditures tended to overstate actual historical expenditures. Additionally, PDFs for profits under IPM and conventional strategies were constructed from the elicited PDFs and used to examine optimal pest control strategies.

Young (1983) used a modified triangular distribution procedure to elicit crop yield distributions tion procedure to elicit crop yield distributions from 272 southeastern Washington and northern Idaho farmers. This procedure was used because the probability elicitation was a small part of a large personal interview questionnaire, and so a quick procedure was needed. Four crops and three tillage systems were considered in the study, and farmers were asked to assess distributions for yields of their dominant crops under each of the three tillage systems. Examples of the questions posed to a farmer growing wheat and peas are:

1. What wheat yield do you expect you are most likely to get if you used this method to grow winter wheat after peas?

2. What do you think your wheat yield would be for the best year out of every ten years if you used this method?

3. What do you think your wheat yield would be for the worst year out of every ten years if you used this method?

The elicitation procedure was found to be both easy and quick to administer, and the results were consistent with results of agronomic field trials in the area.

Pingali and Carlson (1985) compared subjective probability distributions to distributions estimated with historical data and the smoothing technique of Anderson (1973). Subjective probability distributions for fruit damage due to insect, disease and weather were elicited from 28 apple growers in Henderson County, North Carolina. The growers were asked to give the modal value, the lowest value, and the highest value of the percentage of damage they expected from insects, disease and weather. Based on the three points, triangular distributions were identified for each grower for each type of damage. To evaluate the accuracy of the triangular distribution method, the subjective distributions were compared to distributions derived from historical data. The researchers found that, as a group, the growers overestimated average insect and disease damage.

Skees (1986) used the triangular distribution procedure to elicit corn and soybean yield distributions from Kentucky farmers. The mean and standard deviation of the farmers' distributions were compared to the mean and standard deviation of distributions derived from historical yield data for their operations. Results of the study led to the conclusion that, compared to the historically derived distributions, the farmers underestimated expected yields and inaccurately assessed the dispersion of yields.

Griffiths *et al.* (1987) used subjective probability distributions in econometric models of crop response in Nepal. Yield distributions were elicited with the triangular distribution method and were found to correspond closely with distributions elicited with a direct CDF method. Also, subjective means and variances calculated from the triangular distributions were related to production inputs and socio-economic variables. The authors concluded that further conceptual and empirical work is needed on the use of subjective response data in econometric analysis.

A number of indirect techniques have been used in agricultural economics studies. Zering (1985) used an indirect odds method to elicit subjective PDFs for prices and yields of crops produced by a sample of California farmers. Producers were asked to present a range of prices and yields for each crop produced; the ranges were divided into intervals and the producers assigned odds to each interval. Using this information, combined with cost data, probability distributions of net income from different crops for each producer were determined. Then, these distributions were used to predict producers' crop insurance purchase decisions. The predicted number of buyers was low, in part because of a substantial difference between the yield distributions elicited from operators and those used to calculate insurance premiums.

In their Australian study, Francisco and Anderson (1972) used the visual counter method to investigate sheep producers' abilities to assess probability distributions. Twenty one producers in New South Wales were interviewed in order to elicit subjective PDFs for wool price, lamb marking percentage relative to ewes joined, and annual rainfall in inches. Each producer was asked to give a minimum and a maximum value for each of the three variables. This range was divided into several intervals of equal width, and the producers were asked to distribute a total of 25 counters over the different intervals in accordance with the likelihood of occurrence of each interval. As discussed previously, probabilities for each interval were calculated as a ratio of the number of counters assigned to the interval to the total available. The researchers concluded that the producers found the visual counter method acceptable, in that they were readily able to assess probability distributions.

Bessler (1977) elicited subjective probability distributions for barley, wheat and sugar beet yields from a sample of farmers in central California. His objective was to aggregate individual assessments and compare them to historical yield data. In order to estimate PDFs for the crop yields, each farmer was asked to distribute ten discrete probability units over a set of predetermined yield intervals. A scoring rule was constructed which expressed payoffs to the assessor as a function of the distribution of the discrete assessments and the average yield actually experienced by the farmer for the most recent crop year. Aggregated subjective distributions were formed as a simple average of the individual distributions and compared to historical time-series distributions.

Grisley and Kellogg (1983) elicited PDFs for prices, yields and net income for several commodities from 39 farmers in the Chiang Mai valley of northern Thailand. Each farmer was asked, prior to planting, for a minimum and maximum value that each variable could take at harvest. The range was divided into five equal, discrete intervals. Farmers were asked to distribute 25 coins among the five intervals according to the strength of their beliefs that the true value of the variable would fall into any one interval at harvest. Farmers were told that, at harvest time, the actual values of the variables would be checked, and they would be paid the number of coins allocated to the correct interval. The elicited net income distributions for crops produced were analyzed using the stochastic dominance criterion. The stochastic dominance orderings were compared to actual crop production decisions, and the authors concluded that the elicitation approach revealed expectations consistent with actual behaviour.

In a Sri Lankan study, Herath *et al.* (1982) elicited rice farmers' subjective probability distributions for the yields of traditional and modern, high yielding rice varieties using the visual counter elicitation method. The elicited distributions were checked for normality. Most were found not to depart from normality at the 10 per cent level of significance. Those which did were transformed to be approximately normal. Under the assumption of price certainty, net income distributions were obtained from the elicited yield distributions, and were incorporated into decision models to compare three decision criteria: 1) multiattribute utility maximization, 2) single attribute utility maximization, and 3) expected profit maximization.

Lee *et al.* (1985) used a PDF approach to elicit subjective probability distributions for income from a sample of Indiana farmers. Two separate distributions were elicited from each farmer, one for income from conventional tillage practices and one for income from reduced tillage practices. For each distribution, farmers were asked to "distribute 10 probability blocks along an income continuum." The subjective probability distributions were incorporated into stochastic dominance and mean-variance decision criteria and the ability of the criteria to predict tillage decisions was tested. In addition, the predictive abilities of the criteria were compared when subjective and objective (derived from LP farm models) income distributions were used. The researchers found that the decision criteria which used subjective probabilities had a substantially higher level of predictive accuracy than those using objective distributions. Also, using subjective distributions, the stochastic dominance criterion predicted better than the mean-variance criterion.

SriRamaratnam (1985) used subjective probability distributions for grain sorghum prices and yields in an analysis of optimal fertilization rates. Twenty seven producers in the Texas Coastal Bend Region were interviewed to elicit price distributions and yield distributions conditional on four discrete nitrogen fertilizer levels. The elicitation technique used was similar to that of Francisco and Anderson (1972). The ranges of likely prices and yields were divided into a set number of intervals, 10 and 12 respectively. Producers were asked to distribute 20 counters over the intervals according to their price and yield expectations. The producers were told explicitly that each counter represented a 5 per cent chance of any price or yield within the chosen interval occurring, and a scoring rule was used to minimize motivational bias. The elicited yield distributions were generally optimistic (in mean levels) relative to the distributions based on experimental data. The resulting price and yield distributions were incorporated into an expected utility function, and the optimal level of nitrogen fertilizer was determined.

Gibbs *et al.* (1987) used the visual counter method and a variation of the odds method, the partial expectations method, to elicit probability distributions for yields of various wheat varieties in a study of Australian wheat producers. Producers were interviewed at three separate occasions. The objective of the study was to examine the stability of farmers' beliefs and to examine the impacts of new information on farmers beliefs. The researchers analyzed the reliability of the two methods by comparing 1) distributions elicited with a single method at different times, and 2) distributions elicited with each technique to one another (construct validity). They concluded that the partial expectations method was more reliable over time than the visual counter method, although they were unable to rule out the effects of new information on the changing distributions. In testing construct validity, the authors concluded that the two techniques gave different results.

The conviction weights method was used by Pease (1986) to elicit subjective probability distributions from a sample of central Michigan extension agents and cash grain farmers. Using a computer spreadsheet application of the technique, price and yield distributions were elicited for four crops: corn, soybeans, navy beans and wheat. For each crop, the assessors were presented with ranges of prices and yields which were divided into discrete intervals. The assessors were then asked to assign a score of 100 to the interval they felt was most likely to occur. Then, the other intervals were assigned scores from one to 100. (All intervals did not have to be scored.) The scores were converted to probabilities and PDF histograms were displayed by the computer software. The researcher discussed the resulting probabilities with the assessors, and revisions were allowed. The assessors found the method easy to use and responded positively to the use of a computer package to conduct the elicitation procedure. The subjective probability distributions were incorporated into a multiple objective programming model for farm planning.

In another study, Pease (1988) compared the performance of the conviction weights method and a direct CDF method. Both methods were incorporated into an interactive microcomputer programme, and a structured interview process was followed with 98 farm managers. Managers were randomly assigned to one of the elicitation methods. Distributions were elicited for expected corn and soybean yields. Elicitation began at the center of the distribution and proceeded toward the tails, as an attempt to avoid cognitive biases. Assessors were encouraged to reflect on end points and tail probabilities. After the initial input of values, graphical and tabular displays of the subjective distributions were presented on the computer screen. Managers were invited to revise their input after viewing the displays.

As a measure of accuracy, subjective distributions were compared to historical distributions for each farm. Central tendency and dispersion were calculated for elicited distributions and compared with corresponding historical moments. Approximately two-thirds of the subjective means for corn yields were lower than historical means. This result was not affected by the elicitation technique used. Conversely, three-fourths of soybean yield subjective means were greater than historical means, regardless of the elicitation method used. Comparisons of relative dispersion also failed to show any consistent distinction between methods. Pairwise comparison of fit between entire subjective and historical distributions was also conducted using the Kolmogorov-Smirnov test. Results indicated that approximately one-fourth of corn yield subjective distributions and one-third of soybean yield subjective distributions were significantly different from their historical counterparts, again regardless of the method of elicitation. Pease concluded that careful execution of the subjective assessment interview, rather than the choice of elicitation method, is the more critical factor in determining valid measurement of subjective probabilities.

Some Conclusions, Observations and Suggested Applications

There are a number of methods and variants of methods available to agricultural economists for eliciting subjective probabilities. Choice of elicitation technique is an important consideration since the assessor's acceptance of the method as well as the coherence, compatibility, accuracy and reliability of responses may depend on the technique used. Unfortunately, no consensus has emerged in the literature as to the best method to use, although shortcomings of several methods have been identified. Based on the literature reviewed here, some observations can be made for consideration when choosing an elicitation technique. A brief summary of elicitation technique evaluations is provided in Table 2.

There are proponents of both PDF and CDF methods, but the evidence supporting the use of one over the other is not conclusive. Interestingly, of the agricultural economics studies reviewed here, 18 made use of PDF methods while only five elicited CDFs. This suggests that, at the least, researchers have found the PDF methods easier to use.[10] Also, some researchers have found that assessors are more comfortable using PDF methods (Winkler 1967; Chesley 1978; Ludke *et al.* 1977). Where studies have compared subjective probability distributions elicited with PDF techniques to those elicited with CDF techniques, PDF methods have performed better in terms of construct validity and accuracy (Carlson 1970).

The methods reviewed were evenly divided between direct and indirect techniques. Kramer *et al.* (1986) found that farmers preferred a direct PDF approach to an indirect PDF approach, primarily because it took less time. In other studies, however, assessors have found indirect techniques simpler to use (Winkler 1967; Chesley 1978). Researchers who have used both direct methods and indirect methods to elicit probability distributions have generally found little difference between the distributions elicited (Carlson 1970; Pease 1988). It is possible that the decision to use a direct or indirect approach will depend, in part, on the normative expertise of the assessors. Individuals who do not possess a strong understanding of probability may find it difficult to work with probabilities directly.

The accuracy of direct techniques has been evaluated by several researchers. In studies where subjective probability distributions were elicited with a direct technique and compared to historical distributions as a measure of external validity, the researchers found that the subjective and historical distributions did not correspond closely (King 1982; Kramer *et al.* 1986; Pease *et al.* 1988). However, when distributions elicited with indirect techniques have been compared to historical distributions, the indirect methods have also been judged relatively inaccurate (SriRamaratnam 1985).

The direct triangular method has been one of the preferred methods among agricultural economists. This is due, in part perhaps, to the relative ease of administering an elicitation process which requires assessors to express their beliefs in terms of only three values (Young 1983). Griffiths *et al.* (1987) checked construct validity by comparing elicited triangular distributions to directly elicited CDFs. They found that the two corresponded closely. However, in general, the triangular method has not proven accurate when triangular distributions are compared to historical distributions (Hanemann and Farnsworth 1981; Pingali and Carlson 1985; Skees 1986). Furthermore, there is an increased potential for cognitive bias, especially as a result of the anchoring heuristic, in the elicited distributions due to the small number of elicited points on the distribution.

The indirect technique which has been used most widely in agricultural economics research is the visual counter method. Researchers generally have found the technique to be acceptable to assessors (Francisco and Anderson 1972; Grisley and Kellog 1983). However, tests of construct validity and accuracy (using historical distributions as a measure of external validity) have not proved favourable (Gibbs *et al.* 1987; SriRamaratnam 1985). The one study which used the visual counter method to elicit subjective probabilities and compared the resulting distributions to actual outcomes (as a measure of internal validity) concluded that the technique revealed expectations which were consistent with actual behaviour (Grisley and Kellogg 1983).

[10] One cannot rule out the bandwagon effect, however.

Table 2. A Summary of Accuracy, Reliability, Acceptability and Predictive Accuracy Evaluations Made for Elicitation Methods Reviewed, by Method[§]

Method	Event	Accuracy	Reliability	Acceptability	Predictive Accuracy	Reference
Direct PDF	crop loss	0	√	0	0	Carlson (1970)
Direct CDF	crop loss	0	x	0	0	
Gamble (PDF)	crop loss	0	√	0	0	
Direct CDF	yields	0	0	0	√	O'Mara (1971)
Direct PDF	prices	0	0	0	0	Lin (1973)
Direct PDF	yields	0	0	0	0	
Direct CDF	yields	x	0	0	0	King (1982)
Direct PDF	prices	0	0	0	0	Knight (1984)
Direct PDF	yields	x	x	√	0	Kramer *et al*. (1986)
Direct CDF	yields	x	x	√	0	
Visual Counter (PDF)	yields	0	x	x	0	
Triangular (PDF)	yields	√	0	0	0	Hanemann & Farnsworth (1981)
Triangular (PDF)	expenditures	x	0	0	0	
Triangular (PDF)	yields	0	0	√	0	Young (1983)
Triangular (PDF)	crop loss	x	0	0	0	Pingali & Carlson (1985)
Triangular (PDF)	yields	x	0	0	0	Skees (1986)
Triangular (PDF)	yields	0	√	0	0	Griffiths *et al*.(1987)
Direct CDF	yields	0	√	0	0	

Table 2 (cont.).

Odds (PDF)	prices	0	0	0	x	Zering (1985)
Odds (PDF)	yields	0	0	0	x	
Visual Counter (PDF)	price	0	0	√	0	Francisco & Anderson (1972)
Visual Counter (PDF)	yield	0	0	√	0	
Visual Counter (PDF)	rainfall	0	0	√	0	
Visual Counter (PDF)	yields	√	0	0	0	Bessler (1977)
Visual Counter (PDF)	prices	0	0	0	√	Grisley & Kellogg (1983)
Visual Counter (PDF)	yields	0	0	0	√	
Visual Counter (PDF)	income	0	0	0	√	
Visual Counter (PDF)	yields	0	0	0	0	Herath *et al.* (1982)
Visual Counter (PDF)	income	x	0	0	√	Lee et al. (1985)
Visual Counter (PDF)	prices	0	0	0	0	SriRamaratnam (1985)
Visual Counter (PDF)	yields	x	0	0	0	
Visual Counter (PDF)	yields	0	x	0	0	Gibbs et al. (1987)
Partial Expectations (PDF)	yields	0	√	0	0	
Conviction Weights (PDF)	prices	0	0	√	0	Pease (1986)
Conviction Weights (PDF)	yields	0	0	√	0	
Direct CDF	yields	x	0	√	0	Pease (1988)
Conviction Weights (PDF)	yields	x	0	√	0	

[a]Accuracy refers to how well the subjective probability distribution compares to some objective measure of the distribution. Reliability refers to the repetition, stability or consistency of elicited distributions over time or between elicitation techniques. Acceptability refers to how assessors rate the elicitation technique. Predictive accuracy refers to whether using subjective probability distributions improved the predictive ability of decision models. If the criterion was examined in the study, √ indicates positive results and x indicates negative results. A 0 indicates the criterion was not considered.

In examining the predictive ability of decision models using subjective probabilities, Lee *et al.* (1985) found that decision models which incorporated subjective probabilities had a higher level of predictive accuracy than models using historical distributions. O'Mara (1971) found that, using subjective probabilities, his decision model was consistent with observed behaviour. Improving the accuracy of decision models by incorporating the decision maker's beliefs and expectations is a major rationale for the elicitation of subjective probabilities. Based on the limited evidence available, it appears that probability elicitation may improve the predictive accuracy of decision models.

These applications of subjective probability elicitation in agricultural economics research demonstrate opportunities for improving decision analyses and for evaluating extension effectiveness. Most applications have involved the elicitation of price and yield distributions for inclusion in analyses of farmers' production decisions. However, other decisions may rely on subjectively determined price and yield expectations, including the use of storage, forward pricing, hedging and options in marketing programmes. Decision analyses for other risk management tools, for example the purchase of crop insurance, might also benefit from the use of subjective probability distributions.

There are additional opportunities for quantifying uncertainty in management decisions which would entail the elicitation of probability distributions for variables other than commodity prices and yields. Potential applications to agribusiness problems might address demand for businesses' goods and/or services, factor supplies and production costs, and interest rates. Natural resource management issues such as mineral extraction and ground water allocation problems might also provide for applications of the methods reviewed.

Researchers in other fields have laid the groundwork for the successful elicitation of subjective probabilities, and it is clear that a number of useful elicitation methods have been developed. Several agricultural economists have demonstrated the usefulness of these techniques in analyzing economic decisions. However, applications have been limited in scope. Agricultural economics research and extension can benefit by recognizing and making use of the information provided by subjective probabilities. Such probability judgements are a fundamental element of economic decision making.

References

ANDERSON, J.R. (1973), "Sparse data, climatic variability and yield uncertainty in response analysis," *American Journal of Agricultural Economics* 55 (1), 77-82.

ANDERSON, J.R., DILLON, J.L. and HARDAKER, J.B. (1977), *Agricultural Decision Analysis*, Ames, Iowa State University Press.

BEACH, L.R. and PHILLIPS, L.D. (1967), "Subjective probabilities inferred from estimates and bets," *Journal of Experimental Psychology* 75, 354-359.

BESSLER, D.A. (1980), "Aggregated personalistic beliefs on yields of selected crops estimated using ARIMA processes," *American Journal of Agricultural Economics* 62 (4), 666-674.

BESSLER, D.A. (1977), Foresight and Inductive Reasoning: Analysis of Expectations on Economic Variables with California Field Crops, Ph.D. Dissertation, University of California, Davis.

BESSLER, D.A. (1981), *Some Theoretical Considerations on the Elicitation of Subjective Probability*, Department of Agricultural Economics, Purdue University, West Lafayette, Indiana, Station Bulletin No. 332.

BESSLER, D.A. (1984), "Subjective probability," in P.J. BARRY, (ed.), *Risk Management in Agriculture*, Ames, Iowa State University Press.

BRANTHWAITE, A. (1974), "A note comparing three measures of subjective probability, their validity and reliability," *Acta Psychologica* 38 (5), 337-342.

CARLSON, G.A. (1970), "A decision theoretic approach to crop disease prediction and control," *American Journal of Agricultural Economics* 52 (2), 216-223.

CHESLEY, G.R. (1978), "Subjective probability elicitation techniques: a performance comparison," *Journal of Accounting Research* 16 (2), 225-241.

DE FINETTI, B. (1964), "Foresight: its logical laws, its subjective sources," in H.E. KYBURG and H.E. SMOKLER, (eds.), *Studies in Subjective Probability*, New York, Wiley.

DE FINETTI, B. (1970), "Logical foundations and measurement of subjective probability," *Acta Psychologica* 34, 129-145.

DUCHARME, W.M. and DONNELL, M.L. (1973), "Intrasubject comparison of four response modes for subjective probability assessment," *Organizational Behavior and Human Performance* 10 (1), 108-117.

FRANCISCO, E.M. and ANDERSON, J.R. (1972), "Chance and choice west of the Darling," *Australian Journal of Agricultural Economics* 16 (2), 82-93.

GALLANTER, E. (1972), "The direct measurement of utility and subjective probability," *American Journal of Psychology* 16 (2), 208-220.

GIBBS, M., LINDNER, R.K. and FISCHER, A.J. (1987), Reliability of elicited means and variances: a study of farmers' beliefs about wheat yields, Paper presented at the 31st Australian Agricultural Economics Society Conference, Adelaide, South Australia.

GRIFFITHS, W.E., ANDERSON, J.R. and HAMAL, K.B. (1987), "Subjective distributions as econometric response data," *Australian Journal of Agricultural Economics* 31 (2), 127-141.

GRISLEY, W. and KELLOGG, E.D. (1983), "Farmers' subjective probabilities in northern Thailand: an elicitation analysis," *American Journal of Agricultural Economics* 65 (1), 74-82.

GRISLEY, W. and KELLOGG, E.D. (1985), "Farmers' subjective probabilities in northern Thailand: reply," *American Journal of Agricultural Economics* 67 (1), 149-152.

HAMPTON, J.M., MOORE, P.G. and THOMAS, H. (1973), "Subjective probability and its measurement," *Journal of the Royal Statistical Society* A 136 (1), 21-42.

HANEMANN, W.M. and FARNSWORTH, R.L. (1981), The roles of risk preferences and perceptions in the adoption of integrated pest management, Unpublished paper, Department of Agricultural Economics, University of California, Berkeley.

HERATH, H.M.G., HARDAKER, J.B. and ANDERSON, J.R. (1982), "Choice of varieties by Sri Lanka rice farmers: comparing alternative decision models," *American Journal of Agricultural Economics* 64 (1), 87-93.

HOGARTH, R.M. (1975), "Cognitive processes and the assessment of subjective probability distributions," *Journal of the American Statistical Association* 70 (350), 271-289.

HOGARTH, R.M. (1987), *Judgement and Choice: The Psychology of Decision*, Chicester, New York, Wiley.

HUBER, G.P. (1974), "Methods for quantifying subjective probabilities and multi-attribute utilities," *Decision Sciences* 5 (3), 430-458.

HULL, J.C. (1976), "Obtaining probability distributions for the evaluation of investment risk," *Management Accounting* 54 (9), 349-351.

KABUS, I. (1976), "You can bank on uncertainty," *Harvard Business Review* 54 (3), 95-105.

KAHNEMAN, D. and TVERSKY, A. (1973), "Subjective probability: a judgment of representativeness," *Cognitive Psychology* 3 (3), 430-454.

KING, R.P. (1982), Response of dryland wheat farmers to change in the federal All-risk Crop Insurance Program, Unpublished paper, Department of Economics, Colorado State University, Fort Collins.

KNIGHT, T.O. (1984), Evaluation for Extension Programs Using Subjective Probability Distributions and Normative Decision Models, Ph.D. Dissertation, University of Missouri, Columbia.

KNIGHT, T.O., JOHNSON, S.R. and FINLEY, R.M. (1985) "Farmers' subjective probabilities in northern Thailand: comment ", *American Journal of Agricultural Economics* 67(1), 147-148.

KRAMER, R.A., MOORE, J.M. and SRIRAMARATNAM, S. (1986), *Evaluation of federal crop insurance based on farmers' subjective probabilities*, Department of Agricultural Economics, Virginia Polytechnic Institute and State University, Blacksburg, Final Project Report to U.S. Department of Agriculture, Federal Extension Service and Federal Crop Insurance Corporation.

LEE, J., BROWN, D.J. and LOVEJOY, S. (1985), "Stochastic efficiency versus mean-variance criteria as predictors of adoption of reduced tillage," *American Journal of Agricultural Economics* 67 (4), 839-845.

LIN, W. (1973), Decisions Under Uncertainty: An Empirical Application and Test of Decision Theory in Agriculture, Ph.D. Dissertation, University of California, Davis.

LUDKE, R.L., STAUSS, F.F. and GUSTAFSON, D.H. (1977), "Comparison of five methods for estimating subjective probability distributions," *Organizational Behavior and Human Performance* 19 (1), 162-179.

MALCOLM, D. G., ROSEBOOM, J. H., CLARK, C. E. and FAZAR, W. (1959), "Applications of a technique for R and D program evaluation (PERT)," *Operations Research* 7 (5), 646-669.

MODER, J. and RODGERS, E. (1968), "Judgment estimates of the moments of PERT type distributions," *Management Science* 15 (2), B76-B83.

MOSKOWITZ, H. and BULLERS, W.I. (1979), "Modified PERT versus fractile assessment of subjective probability distributions," *Organizational Behavior and Human Performance* 24 (2), 167-194.

MURPHY, A.H. and WINKLER, R.L. (1984), "Probability forecasting in meteorology," *Journal of the American Statistical Association* 79 (387), 489-500.

NELSON, A.G. and HARRIS, T.D. (1978), "Designing an instructional package: the use of probabilities in farm decision making, " *American Journal of Agricultural Economics* 60 (5), 993-997.

O'MARA, G.T. (1971), A Decision-Theoretic View of the Microeconomics of Technique Diffusion in a Developing Country, PhD. Dissertation, Stanford University.

PEASE, J.W. (1986), Multiple Objective Decision Support for Farm Managers, Ph.D. Dissertation, Michigan State University, East Lansing.

PEASE, J.W. (1988), *Yield forecasts using historical and subjective farm level data*, SP88-37, Department of Agricultural Economics, Virginia Polytechnic Institute and State University, Blacksburg.

PINGALI, P.L. and CARLSON, G.A. (1985), "Human capital, adjustments in subjective probabilities and the demand for pest controls," *American Journal of Agricultural Economics* 67 (4), 853-861.

SAVAGE, L.J. (1971), "Elicitation of personal probabilities and expectations," *Journal of the American Statistical Association* 66 (336), 783-801.

SAVAGE, L.J. (1954), *The Foundations of Statistics*, New York, Wiley and Sons.

SCHAEFER, R.E. (1976), "The evaluation of individual and aggregated subjective probability distributions," *Organizational Behavior and Human Performance* 17 (2), 199-210.

SCHAEFER, R.E. and BORCHERDING, K. (1973), "The assessment of subjective probability distributions: a training experiment," *Acta Psychologica* 37 (2), 117-129.

SCHLAIFER, R. (1959), *Probability and Statistics for Business Decisions*, New York, McGraw-Hill.

SCHLAIFER, R. (1969), *Analysis of Decisions Under Uncertainty*, New York, McGraw Hill.

SEAVER, D.A., VON WINTERFELDT, D. and EDWARDS, W. (1978), "Eliciting subjective probability distributions on continuous variables," *Organizational Behavior and Human Performance* 21 (3), 379-391.

SIMS, C.A. (1982), *Scientific standards in econometric modelling*, Discussion Paper No. 82-160, Center for Economic Research, Department of Economics, University of Minnesota, St. Paul.

SKEES, J.R. (1986), *Comparing objective and subjective yield estimates: an empirical study in western Kentucky*, Staff Paper 198, Department of Agricultural Economics, University of Kentucky, Lexington.

SMITH, L.H. (1967), "Ranking procedures and subjective probability distributions," *Management Science* 14 (4), 236-249.

SONKA, S.T. and PATRICK, G.F. (1984), "Risk management and decision making in agricultural firms," in P.J. BARRY, (ed.), *Risk Management in Agriculture*, Ames, Iowa State University Press.

SPETZLER, C.S. and STAEL VON HOLSTEIN, C.-A.S. (1975), "Probability encoding in decision analysis," *Management Science* 22 (3), 340-358.

SRIRAMARATNAM S. (1985), Texas Coastal Bend Grain Sorghum Producers' Fertilizer Decisions Under Uncertainty, Ph.D. Dissertation, Texas A&M University, College Station.

STAEL VON HOLSTEIN, C.-A.S. (1970), *Assessment and Evaluation of Subjective Probability Distributions*, The Economic Research Institute at the Stockholm School of Economics, Stockholm.

STAEL VON HOLSTEIN, C.-A.S. (1972), "Probabilistic forecasting: an experiment related to the stock market," *Organization Behavior and Human Performance* 8(1), 139-158.

STAEL VON HOLSTEIN, C.-A.S. and MATHESON, J.E. (1979), *A Manual for Encoding Probability Distributions*, SRI International, Menlo Park, California.

TVERSKY, A. and KAHNEMANN, D. (1975), "Judgement under uncertainty: heuristics and biases," in D. WENDT and C. VLEK, (eds.), *Utility, Probability, and Human Decision Making*, Boston, D. Reidel Publishing Company.

WALLSTEN, T.S. and BUDESCU, D.V. (1983), "Encoding subjective probabilities: a psychological and psychometric review," *Management Science* 29 (2), 151-173.

WINKLER, R.L. (1972), *An Introduction to Bayesian Inference and Decision*, New York, Holt, Rinehart and Winston.

WINKLER, R.L. (1967), "The assessment of prior distributions in bayesian analysis," *Journal of the American Statistical Association* 62 (319), 776-800.

WINKLER, R.L. and MURPHY, A.H. (1968), "Good probability assessors," *Journal of Applied Meteorology* 7 (5), 751-758.

YOUNG, D.L. (1983), A practical procedure for eliciting subjective probability distributions, paper prepared for the annual American Economics Association meeting, West Lafayette, Indiana.

ZERING, K.D. (1985), The Utility of All-risk Crop Insurance in the Imperial Valley of California, Ph.D. Dissertation, University of California, Davis.