THE ACCURACY OF PRODUCER EXPECTATIONS: EVIDENCE AND IMPLICATIONS FOR INSURANCE VALUATION

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The Accuracy of Producers' Probability Beliefs: Evidence and Implications for Insurance Valuation

by

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Abstract

The accuracy of producer's probability beliefs is examined through a survey of large cash-grain farmers in Illinois. It is found that their subjective probability beliefs about important weather variables are systematically miscalibrated to the true distributions. The nature and extent of the differences between their subjective and true probability measures are shown empirically, and through fitted calibration functions. The economic significance of inaccurate subjective probability beliefs is established in the context of insurance valuation by producers. The results demonstrate that significant errors in producers' risk assessments and insurance valuation arise simply from the fact that producers possess systematically inaccurate probability beliefs.

Keywords: precipitation insurance valuation, probability beliefs, risk assessment

Introduction

Significant resources have been devoted to the development and evaluation of agricultural risk-management products, with particular attention paid to crop yield, and crop revenue insurance contracts. Numerous studies have carefully examined the empirical distributions of crop yields and prices, and have developed various insurance valuation models that are equipped to deal with the resulting risk specifications (Day; Gallagher; Goodwin and Ker; Ker and Goodwin; Nelson; Stokes). On the behavioral side, moral hazard and adverse selection issues have also been carefully assessed and incorporated into explanations of the performance of popular insurance products, and into empirical and theoretical studies of crop insurance demand (Coble, Knight, Pope, and Williams; Just, Calvin, and Quiggin; Smith and Goodwin; and Skees and Reed; and many others). While the bulk of the applications in agriculture have understandably targeted the large array of Federal Crop Insurance Corporation (FCIC) products, there has also been a rapidly increasing interest in the use of weather derivatives as mechanisms to manage specific agricultural risks. To date, the weather derivative market has developed much more rapidly in energy applications, and in insurance for outdoor public events, but studies that parallel crop insurance methods to evaluate weather insurance are also beginning to appear in the literature (Martin, Barnett and Coble; Dischel; Sakurai and Reardon; Turvey; Changnon and Changnon). Importantly, the vast majority of the existing crop insurance and risk management literature is underpinned with the assumption that producers accurately understand and rationally respond to the risks they face.

This research explores the important, but frequently unexamined assumption that producers possess accurate probability beliefs when evaluating risky variables that affect their financial well-being. To do so, a survey designed to elicit subjective probability beliefs about important weather variables that influence producers' well-being was administered to a set of producers. The recovered subjective probability beliefs are then compared to actual weather event distributions in both empirical and fitted form. Then, calibration functions are estimated to provide insight into the extent and nature of the differences between the "true" probability distribution and individuals' subjective probability measures. Standard precipitation insurance contracts are evaluated to demonstrate the economic significance of the differences between the producers' belief sets and the underlying true distributions of interest. Weather variables are focused on due to their ubiquity, relevance to crop farmers, impossibility of influence by producers, and widely available existing information to condition decision makers' priors. Further, insurance on weather variables naturally limits adverse selection and moral hazard influences, and thus isolates the impacts of inaccurate priors in a relatively straight-forward fashion.

The remainder of the paper is organized as follows. Results are first presented from a survey that was used to elicit subjective climate expectations from a sample of agricultural producers. The producers' subjective probability beliefs are first compared directly to "true" probabilities at several points on the underlying distribution. Then, calibration functions are fit to provide insights into the nature of the differences between the subjective and historic probability measures. Thereafter, the implications of the differences are developed in terms their impacts on insurance valuation. A summary and concluding remarks complete the paper.

Expectations of Climate Variables Survey

A survey was conducted to recover complete probabilistic descriptions of producers' climate expectations. Participants were selected for their: 1) cooperation with the Illinois Farm Business - Farm Management (FBFM) record keeping association, 2) proximity to a single weather reporting station (to mitigate the potential effects of widely differing experiences, all were in a territory covered by a single NOAA weather reporting station), 3) being relatively large cash grain operations, and 4) demonstrated understanding of probability concepts. Personal interviewers elicited producers' perceptions of the long-run probabilities of rainfall at various levels through a series of questions posed in both the cumulative distribution function (CDF) framework and inverse CDF framework. Numerous questions were recast throughout the survey to locate any changes in perceptions or misperceptions of the intent of questions. For example, if a respondent indicated that the level of rainfall at which the 25th cumulative percentile occurred was 2", the enumerator would later ask for the probability that 2" would be exceeded to insure that the respondent replied in a manner consistent with the earlier answer. A pretest was administered to insure comfort and adequate facility with probabilistic concepts, and internal checks were constructed to insure that the respondents' probability measures were indeed consistent and representative of their beliefs. The survey included approximately 12 categories of variables that affected the producer's financial well-being and took approximately one hour plus pretest time per respondent to administer. A total of fifty-four surveys were administered and processed into useable form .[1] Among the specific climate variables of interest included in the survey are April rainfall and July rainfall.[2] Higher April precipitation is considered by Illinois crop producers to be a negative event as it tends to delay planting. Conversely, July precipitation is a positive event, as it tends to enhances crop growth and reproduction during a crucial phase of reproduction. These two variables were chosen because of their particular importance to grain farmers, and because the effects on the respondents are of opposite sign thus generating a natural contrast for study of the accuracy of their probability beliefs.

Weather Variable Representations

A distributional representation is needed to summarize information from the historic weather data, and to provide a more complete description of each producer's subjective probability beliefs. A distribution that has been used extensively in various forms to model precipitation amounts, as a function for business losses, and by the insurance industry as a candidate for loss distributions is the Burr-12 distribution, also sometimes referred to as a 3-parameter Kappa distribution in weather applications (Mielke; Mielke and Johnson; Tadikamalla). The Burr has zero support, may take on a wide range of skewness and kurtosis, and can be used to fit almost any set of unimodal data (Tadikamalla, 1980). The Burr distribution is highly flexible and contains the Pearson types IV, VI, and bell-shaped curves of type-I, gamma, Weibull, normal, lognormal, exponential, and logistic distributions as special cases (Rodriguez; Tadikamalla). Because of this flexibility, it is widely accepted in the climate literature as a representation for precipitation levels, and was used to represent the true distribution and each producer's underlying subjective distribution.[3] The Burr probability density function (PDF) and cumulative distribution function CDF for rainfall, Y, with parameters α, λ, and τ, are respectively:

(1) $$f(y) = \tau\lambda\alpha^{-1}(y/\alpha)^{\lambda-1}(1+(y/\alpha)^{\lambda})^{-(\tau+1)}, \quad y,\alpha,\lambda,\tau > 0$$

(2) $$F(y) = 1-(1+(y/\alpha)^{\lambda})^{-\tau}$$

Monthly data from the National Climatic Data Center on rainfall totals from 1900 to 2000 at the East Central Illinois weather reporting station were used to estimate the parameters of the true distributions of April and July rainfall using maximum likelihood estimation. Parameters for each producer's subjective probability measures for both April and July rainfall were also estimated under the same parametric assumptions using nonlinear least squares between implied and tabulated response quantiles.

Results

Figure 1 depicts the subjective beliefs about precipitation levels for a selected set of respondents with differing types of probability beliefs. As can be seen in the graph, different forms of miscalibration or incongruence between historic and subjective measures exist. For example, farmers #5 and #47 believed the density of April precipitation to be more spread out and have a higher median than the true (these two represent the most common responses relative to April precipitation). Farmers #19 and #25 have subjective probability measures that are generally shifted to a lower level than the true, but with a somewhat longer right hand tails. Respondent #44 displays overconfidence, and a slightly elevated central tendency.

Relative to July precipitation, respondent #25 has a higher median while the others each have subjective beliefs with medians lower than the true. Respondent #47 displays extremely high pessimism with highly overstated probability of zero or no rainfall. Respondent #44 represents a typical response for July rainfall with a median that is below the true and somewhat understated probabilities at the high range. Respondent #5 has fairly accurate probability beliefs relative to July rainfall. The cumulative distribution functions are provided as well for convenience in interpretation.

The respondents depicted in the graphs are not meant to be representative of the entire sample, but were chosen simply to illustrate the nature of the information retrieved and to help understand the types of differences both among their responses and between their individual beliefs and the historic measures.

[see figure 1]

Table 1 summarizes the farmer responses across the entire sample for both April and July precipitation. Several quantiles are tabulated under which the farmers' responses are summarized and compared to the actual precipitation values. For example, for April precipitation at the 25th percentile, the precipitation level corresponding to the true distribution is 2.30 inches. In other words, there is a 75% chance of receiving at least 2.30 inches of precipitation in the month of April in this weather reporting district. Of the farmers surveyed, 63% expected more precipitation at the 25th percentile. The average of all responses at the 25th percentile of the distribution was 2.77 inches. Note that the average of the expected precipitation is greater than the true amount at all percentile levels, although by only a slight amount at the 10-percentile level. Clearly, the subjective probabilities elicited from this group of farmer respondents generally overweighted what they perceive as the negative event of excess April precipitation, with the fraction overstating the rainfall higher at levels generally considered less desirable. If the respondents had no systematic bias in their beliefs, then the percentage overstating the median might reasonably have been expected to be around 50%, but the miscalibration of the sample appears to be systematically toward overstated levels of precipitation. The standard deviation across responses at each quantile is also provided to show the degree of agreement among respondents at each level.

The respondents' subjective probability beliefs July precipitation follow a different – yet still pessimistic – pattern. In this case, more rainfall is considered to be a good event, and the respondents generally understate the likelihoods of occurrence. As can be seen in table 1, only 22% of the respondents overstated the quantity of rainfall at the 25th percentile of the actual distribution. In fact, at each percentile level, the farmers understated the incidence of precipitation,or equivalently, overstate the probability of what would be viewed as the negative event – lack of precipitation.

[see table 1]

Individual Producer Calibration Tests

In addition to the information available in Table 1 that summarizes the entire set of respondents, it is useful to develop more descriptive measures of differences between individual producers' subjective beliefs and the true. And, in cases that exhibit significant differences, it is useful to more completely describe the nature and extent of the difference between subjective and actual distributions over different percentile levels or among differing events. For example, a producer may be very good at forecasting the likelihood of a low-rainfall event, but be poor at assigning probabilities to large-rainfall events. Or, the producer may have more accurate priors about April than July rainfall. Because risk management activities often focus only on ranges of adverse outcomes, it would useful to be able to describe the congruence between actual and subjective probability beliefs in specific regions of interest. To address these and related issues, calibration functions were estimated.

Calibration in this context refers to the correspondence between a predicted and an actual event. In terms of distributions, calibration describes how close the predicted and resulting functions are. Heuristically, the adjustment that is required to make the subjective beliefs correspond to the true distribution is termed the calibration function. Specifically, if the true distribution can be described as $\varphi(x)$ and the estimated function is $F(x)$, then $K(F(x)) = \varphi(x)$ implicitly defines a transformation, $K(\bullet)$ of F, to generate estimates, $K(F(x))$, that are well calibrated. The function $K(\bullet)$ is called the calibration function. A parametric form can be chosen for the calibration function and estimated using standard methods, with the resulting shape of the estimated function used to interpret the nature of the miscalibration (Fackler and King).

For the purposes of this study, the calibration function is based on the beta distribution with density:

$$(3) \qquad K(x) = x^{p-1}(1-x)^{q-1} \big/ \beta(p,q),$$

where $\beta(p,q)$ is the beta function with parameters p and q. As noted in Fackler and King, the Beta distribution is well known, flexible and contains the uniform distribution as a special case when $p = q = 1$, implying perfect calibration. A simple test for calibration may be performed by testing the uniformity of K, for if $F(\bullet)$ is already well calibrated, K is simply a uniform mapping. Regions of $K(\bullet)$ with slope greater than one correspond to regions of the subjective probability CDFs that need to have mass added, and regions of $K(\bullet)$ with slope less than one correspond to regions of the subjective distribution that have too much mass and need to be decreased. Other shapes of the fitted calibration curve similarly indicate the "reweighting" of the estimated distributions needed to correspond to those subsequently observed.

At least 5 general shapes for the calibration function emerge that summarize the nature of the miscalibration displayed by each individual. Figure 2 displays the sample calibration functions corresponding to the following cases: (1) well calibrated or uniform, $p = q = 1$; (2) underconfidence or an overstatement of dispersion, $p > 1$, $q > 1$; (3) overconfidence or an understatement of dispersion, $p < 1, q < 1$; (4) understatement of location $p > 1, q < 1$; and (5) overstatement of location, $p < 1, q > 1$. Because the slope of the calibration function reflects the reweighting of the subjective distribution that is needed to make it correspond to the true distribution, the uniform case (1) is a straight line with slope 1 throughout and therefore leaves the subjective beliefs unchanged. Case 2 is an "S-shaped" function that takes mass away from the tails (where the slope is less than one) and adds it to the interior region where the slope is greater than one. Case 3, by contrast, is a "reverse-S" shaped function that spreads the mass out by adding to the tails and reducing the central region where the calibration function slope is less than one. Case 4 is a "U-shaped" function that shifts mass to the right, and case 5 is a n "inverted-U" shape that shifts mass to the left. The median is located correctly when p=q (cases 1,2,and 3 as shown), but the calibration function can also cross the uniform from above or below at locations other than at $F(y)$ = .5 indicating miscalibration in both location and dispersion.

[see figure 2]

Calibration functions were estimated for each participant's subjective distribution for both April and July rainfall using least squares between the recalibrated beliefs and the true at each percentile level surveyed. Table 2 contains the summary of the results organized into two sections with the upper panel simply reporting the parameter pairings from which general shapes can be inferred, and the lower panel giving more specific information about two attributes – median location and dispersion – that help understand the degree and nature of the miscalibration. As shown in the table, the most prominent recalibration needed for the April subjective distributions is to shift the mass to the left (inverted-U) and for July, the most common fitted calibration function indicates that the mass of the probability distributions need to be shifted to the right ((U-shaped). These shifts can occur in conjunction with either increases or decreases in dispersion, and thus it is also useful to tabulate the more general effects. The lower panel provides evidence about combined attributes representing location and dispersion. The top two rows can be added together to get all the cases with median overstated (and can also be read from the 50th percentile column in table 1), while the lower two rows can be summed to get cases with the median understated. The first and third row contain all the cases with dispersion overstated, while the second and fourth row show the cases with dispersion understated. As seen in the table, the 72% of the April sample with overstated location is more heavily weighted toward overstated dispersion as well – both attributes that overstate risk. Of the 74% of the July sample that understated the location, the sample is more heavily weighted toward understatement of dispersion. The final line indicates the number of subjective distributions that are considered to be well calibrated based on likelihood ratio tests of the fitted calibration function against a uniform null, with approximately 9% and 15% of the responses considered well calibrated for April and July respectively.

In addition to the results for individual responses, calibration functions were also estimated for the simple average of all respondents. In the case of April, the resulting calibration function has an "inverted-U" shape, understating the location while overstating the dispersion. For July, the calibration function for the average response across producers displays a "U-shape" with a slightly understated dispersion.

It is apparent from both the tabulated survey results and the calibration tests that producers tended to overstate the amount of rainfall in April and understate that in July – both undesirable events are overstated. Further, the calibration tests indicate that dispersion in the subjective rainfall distributions has a tendency to be understated in the case of July and overstated in the case of April rainfall. The general beliefs are systematically what could be termed "pessimistic" rather than simply being misstated in a manner that applies regardless of the event being considered. Again, if there were simply a "naive" mistake process manifested, it would have been more likely that the types of mistakes would have been consistent between the two events rather than displaying the upward bias in April and the downward bias in July probabilities as was found.

Implications for insurance valuation

The impact of inaccurate priors depends both on the degree of difference from the true and on specific context in which the information is used. It could be the case that small inaccuracies have substantial consequences in risk management, or it could be that the decision rules are such that the probability beliefs are relatively inconsequential and have little economic impact. To demonstrate the potential economic importance of having miscalibrated probability beliefs about weather variables, precipitation insurance is evaluated under the each producer's fitted probability beliefs and compared to the actuarial value calculated under the true. The differences can then be viewed as direct measures of the potential economic impact of the inaccurate prior beliefs.

The most common forms of precipitation insurance can be valued in analogous manner to standard option pricing approaches. Numerous precipitation guarantee valuation models have been developed elsewhere in the literature to take advantage of specific attributes of producer demand, but most are developed in terms of the expected loss functions (Martin, Barnett, and Coble; Turvey; Aquila; Dischon).

Typically, an insured event, such as cumulative precipitation in a specified interval of time, is offered for insurance at various trigger points or strike prices, and at a fixed liability for each unit of excess or deficit. In the current context, rainfall totals measured at a single weather reporting station during the months of April and July are the insured events. The indemnity triggers, often termed strikes or *k*, could be offered at either producer selected levels or at standardized increments, for example at 2.5", 3.0", 3.5" and so on. As is typical, the insurance contract is written to pay a constant, λ, times the amount by which the insured event exceeds the trigger, k, and make no payments if the trigger is not exceeded. The scale of λ is chosen to make the contract magnitude meaningful to the users, and in the case of rainfall insurance, multiples of $1,000 are commonly used. The strike prices are set to provide a meaningful "menu" to appeal to producers with differing needs. For instance, a producer with a large machinery base, and light soils may consider excess rainfall less of a problem than a producer who needs more workable field days to put in a crop. The first farmer described might prefer a relatively high strike compared to the latter farmer to more nearly mimic the points at which each begins to suffer economic losses due to excess rainfall.

The indemnity payoff function for excess rainfall can be written as $max\{0, y-k\}*\lambda$ where y is the realized rainfall total. Given a probability measure, $f(y)$ governing the rainfall outcome, y, the expected (actuarial) value, V_r of the excess rainfall insurance contract is:

$$(4) \qquad V_r = \lambda * \int_k^{\infty} (y - k) f(y) dy$$

Similarly, July-drought insurance is evaluated that pays λ per inch of rainfall deficit to k during the month of July with a resulting indemnity function of $max\{0,k-y\}*\lambda$. The actuarial value, V_d of such a contract can thus be found by evaluating:

$$(5) \qquad V_d = \lambda * \int_0^{k} (k - y) f(y) dy$$

The values of insurance against excess April rainfall were calculated using equation [4] across strike prices from 2 inches to 10.5 inches in half-inch increments, and using λ = $1000. At each strike, the valuation equation was applied using the estimated actual rainfall distribution for $f(y)$ and then repeated using each producer's subjective beliefs to describe the probability measure *f(y).* The result is one valuation relationship for each farmer, and the actuarial values at each strike against which they can be compared.

Table 3 contains the complete results of the actuarial calculations and producer valuation results for insurance against excess rainfall in April. The first two columns gives the strike price or level of rainfall insured against, and the associated probability of triggering the insurance under the actual rainfall distribution. The third column contains actuarially fair values of insurance, (expected costs) which range from approximately $1,895 at a 2" strike price, down to only $1.39 per $1,000/in. coverage at a strike of 10.5 inches. As can be seen in the table, for example, the actuarially fair payments to a policy holder who insures at a strike price of 5 inches would be $347.93. The fourth column contains the average across all respondents of their perceived probability of triggering insurance payments at that strike. Comparison to the second column provides a direct indication of the mistakes in risk assessment that arise from miscalibrated beliefs.

The fifth column contains the average implied values of insurance at each strike. Interestingly, this group of producers, on average, overvalued the risk-costs associated with rainfall at every level tabulated. The difference at the actuarially fair point is due solely to misperceptions of the risks faced, in this case resulting in perceived values of insurance that exceed the actuarial values by $631 (33%) at the 2" strike, to $611 (40%) at the 2.5 inch strike and so on to the point that the overstatement is nearly 35 times the actual value at a strike of 10.5 inches. While the dollar value of the error declines with the strike, the percentage overstatement explodes as the actuarial value approaches zero. Under either case, it is clear that respondents overestimate the risks associated with what is perceived to be the negative event of excess April rainfall. The next column labeled "*% Respondents who overvalue*" gives the percentage of respondents whose implied values under their subjective probability distributions are greater than the value under the true distribution. Across the sample, roughly 70% of the respondents overvalued the insurance. Because the different perceptions of risks result in different implied values, it is reasonable to expect different responses to the availability of such insurance. For instance, it could be reasonable to expect that only those who perceived themselves to have a positive expected payoff to insurance to buy, and at the strike price for which the positive expected payoff were greatest. This form of self-selection may be viewed as favorable adverse selection to the producers, but is really just a result of having inaccurate probability beliefs.[4] Nonetheless, assuming that only those whose implied values exceed the actuarial values actually purchase the insurance produces even more striking results. The column in table 3 labeled "*Ave Value given overstated*" tabulates the averages of the perceived values at each strike for the subset of producers whose implied insurance values are greater than the actuarial value. As seen, the dollar valued overstatement is greatest at the lower strikes and declines as the probability interval evaluated in the insurance decreases. The percentage overstatement in value is near 100% at 3.5", a strike that is nearly at the mean of the actual distribution.

Table 4 presents comparable results for July drought insurance with λ = \$1000. The table is constructed across strikes from .5 inches to 5 inches in half-inch increments. The probability range covered in this interval is from approximately 1% likelihood or a 1 in 100 years drought event to 5", covering the outcomes of nearly three-quarters of all years. Actuarially fair insurance at the 3.25" level has a value of approximately \$638, as shown. The producers again substantially overstate the probability of needing the insurance (triggering payment), and overvalue the risks of drought across all farmers at every strike tabulated, with the greatest percentage overvaluation occurring at the extreme low range of the outcome distribution. The percentage of respondents who overvalue the insurance is not as great as was the case with April excess rainfall insurance, but still exceeds 50% across the entire range of outcomes. As earlier, the percentage and value of the differences between the producers' valuations and the actuarial valuations are very large. Again, the results demonstrate that inaccurate probability beliefs of the nature possessed by the producers in this sample can have a significant impact on the evaluation of risk.

Figures 3 and 4 summarize the results for the actuarial value, average across all farmers, and the average across farmers who would self select insurance based on having overstated expected values of insurance for April and July respectively. The figures take on the familiar shapes of traditional option or insurance values as expected. The graph extends what is found through the calibration tests by converting the differences to measures that have economic interpretation as well – the value of insurance at different strike prices. Although only the averages are shown, it is worth noting that the valuation relationships for the individuals vary greatly with the majority plotting substantially above the actuarial level, and a few that plot either below, or cross from below to above the actuarial relationship. From both the averages and the individual results, it is clear that the farmers substantially overstate the value of this type of insurance due to their miscalibrated beliefs about adverse outcomes.

Summary and Conclusions

Much effort has been devoted to evaluation of production insurance of various forms and on other risk management tools. However, relatively little attention has been paid to what could be called the starting point of that line of reasoning -- that subjective beliefs held by the decision makers are accurate. The results from this study indicate that producers have systematically inaccurate beliefs about variables that have important impacts on their financial well-being. The differences between subjective priors and the actual weather event distributions are highly varied, but display the tendency across respondents to overstate likelihoods for negative events and thus understate the incidence of positive events. Despite the wide differences in beliefs, they commonly lead to substantial overvaluation of both excess rainfall insurance during planting, and drought insurance during a critical phase of crop development.

The results, are of course, subject to limitations of the data, but nonetheless are important in that they challenge the use of the assumption that producers accurately understand, and therefore can rationally respond to, production risks faced. The implications to precipitation insurance are direct in that the differences can lead to substantial overstatement of the value of insurance, and that there could be significant self selection of participation due solely to differences in the producer perceptions of the risks faced. More generally, the results suggest that those designing new insurance and risk management tools should include the potential effects of inaccurate risk assessments by users in their considerations of demand and usage. And, interestingly, in cases where inaccurate beliefs would lead to underusage of insurance, it may be more effective to educate potential users about the actual risks faced than to subsidize the products to the point that they appear attractive even with miscalibrated beliefs. This point may be especially relevant to the design of crop yield insurance programs, where some evidence exists that farmers expect yields that are too high relative to the true, and as a result understate the probabilities of very low yields.

Future research should examine a similar question with regard to producers' perceptions of other risky variables, with particular attention paid to producers' beliefs about yield and revenue risks, and the impact of potential inaccuracies on the demand for yield and revenue insurance products. Other extensions could likewise investigate the role of beliefs about risk in input usage and marketing behavior, to identify but two other cases where the assumption that producers' beliefs are accurate may deserve further consideration. In any case, what is clear from these results is that the assumption that producers possess accurate understanding of the risks they face should not be accepted without further scrutiny of the potential types of miscalibrations of beliefs that might exist, and the potential effects on their assessments and responses to risk.

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Table 1. Summary of farmers' subjective probability beliefs relative to true probabilities

	Percentile Level				
	10%	25%	50%	75%	90%
April Precipitation					
True (inches)	1.40	2.30	3.55	4.98	6.39
Average farmer response (inches)	1.41	2.77	4.47	5.85	7.53
% of responses greater than actual	53.7%	63.0%	72.2%	74.1%	64.8%
Std. dev. across respondents	0.56	1.02	1.24	1.45	2.07
July Precipitation					
True (inches)	1.12	2.02	3.42	5.14	6.93
Average response	0.81	1.79	3.03	4.65	6.18
% of responses greater than actual	16.7%	22.2%	25.9%	42.6%	38.9%
Std. dev. across respondents	0.54	0.72	0.84	1.19	2.27

Table 2. Calibration Functions Summary

Fitted and Empirical Calibration features	April Precip. % Farmers	July Precip. % of Farmers
"U"-shaped calibration function	20.4%	51.9%
"Inverted U"-shaped calibration function	61.1%	20.4%
"S"- shaped calibration function	11.1%	14.8%
"Reverse S"-shaped calibration function	7.41%	13.0%
Median overstated and Dispersion overstated	57.4%	20.4%
Median overstated and Dispersion understated	14.8%	5.6%
Median understated and Dispersion overstated	7.4%	16.7%
Median understated and Dispersion understated	20.4%	57.4%
Well calibrated*	9.3%	14.8%

#Dispersion considered overstated if calibration function indicates that the probability in the interquartile range is understated by farmer (slope of calibration function greater than one over range). Dispersion measured by standard deviation of fitted relative to true gives similar results.

* Likelihood ratio test of fitted calibration function is insignificantly different from uniform at a 95% level of confidence and therefore considered to be well-calibrated

Table 3. April excess rainfall insurance: actuarial values and producer valuation summary

Strike (inches)	Prob. rain > k	Actuarial Insurance ($)	Subjective prob. rain > k	Ave Value to Producer ($)	Ave % Misvalued	% Respondents who overvalue	Ave Value Given overstated ($)	Self selected % overvalued
2.0	0.806	1,895.31	0.859	2,525.93	33%	74%	2,925.52	54%
2.5	0.712	1,515.31	0.787	2,126.21	40%	74%	2,506.79	65%
3.0	0.611	1,184.37	0.706	1,766.73	49%	74%	2,121.68	79%
3.5	0.509	904.36	0.621	1,451.01	60%	72%	1,798.29	99%
4.0	0.412	674.19	0.535	1,179.97	75%	72%	1,490.14	121%
4.5	0.324	490.42	0.451	951.79	94%	72%	1,221.84	149%
5.0	0.248	347.93	0.373	762.54	119%	67%	1,047.63	201%
5.5	0.184	240.63	0.302	607.45	152%	65%	866.74	260%
6.0	0.132	162.17	0.239	481.68	197%	69%	670.33	313%
6.5	0.092	106.47	0.186	380.55	257%	69%	536.43	404%
7.0	0.063	68.07	0.141	299.73	340%	69%	426.85	527%
7.5	0.041	42.37	0.105	235.41	456%	69%	337.81	697%
8.0	0.026	25.67	0.077	184.32	618%	67%	272.70	962%
8.5	0.016	15.13	0.055	143.79	850%	67%	213.74	1,312%
9.0	0.010	8.68	0.038	111.65	1,186%	67%	166.54	1,818%
9.5	0.006	4.84	0.026	86.16	1,679%	67%	128.83	2,560%
10.0	0.003	2.63	0.018	65.97	2,410%	65%	101.53	3,763%
10.5	0.002	1.39	0.012	50.00	3,505%	63%	79.26	5,616%

Table 4. July rainfall deficit insurance: actuarial values and producer valuation summary

Strike (inches)	Prob. rain < k	Actuarial Insurance ($)	Subjective prob. rain < k	Ave Value to Producer ($)	Ave % Misvalued	% Respondents who overvalue	Ave Value Given overstated ($)	Self selected % overvalued
0.50	0.026	4.91	0.055	12.67	158%	57%	20.17	311%
0.75	0.052	14.53	0.092	30.98	113%	59%	46.66	221%
1.00	0.083	31.23	0.134	59.10	89%	59%	86.49	177%
1.25	0.119	56.31	0.179	98.04	74%	63%	135.01	140%
1.50	0.158	90.79	0.226	148.58	64%	63%	200.46	121%
1.75	0.200	135.47	0.276	211.29	56%	65%	275.56	103%
2.00	0.244	190.93	0.326	286.53	50%	67%	362.82	90%
2.25	0.289	257.57	0.377	374.44	45%	67%	468.04	82%
2.50	0.335	335.63	0.427	474.99	42%	67%	586.41	75%
2.75	0.381	425.17	0.476	587.96	38%	69%	709.89	67%
3.00	0.427	526.14	0.524	712.98	36%	69%	852.34	62%
3.25	0.471	638.35	0.569	849.53	33%	69%	1,006.20	58%
3.50	0.514	761.52	0.611	996.97	31%	70%	1,160.71	52%
3.75	0.556	895.30	0.650	1154.61	29%	70%	1,334.72	49%
4.00	0.596	1,039.25	0.686	1321.68	27%	72%	1,505.16	45%
4.25	0.633	1,192.88	0.719	1497.39	26%	72%	1,695.14	42%
4.50	0.669	1,355.67	0.749	1680.94	24%	72%	1,892.45	40%
4.75	0.702	1,527.07	0.776	1871.59	23%	72%	2,095.90	37%
5.00	0.733	1,706.50	0.800	2068.59	21%	72%	2,304.73	35%

Figure 1. Actual and producer probability measures for April and July rainfall.

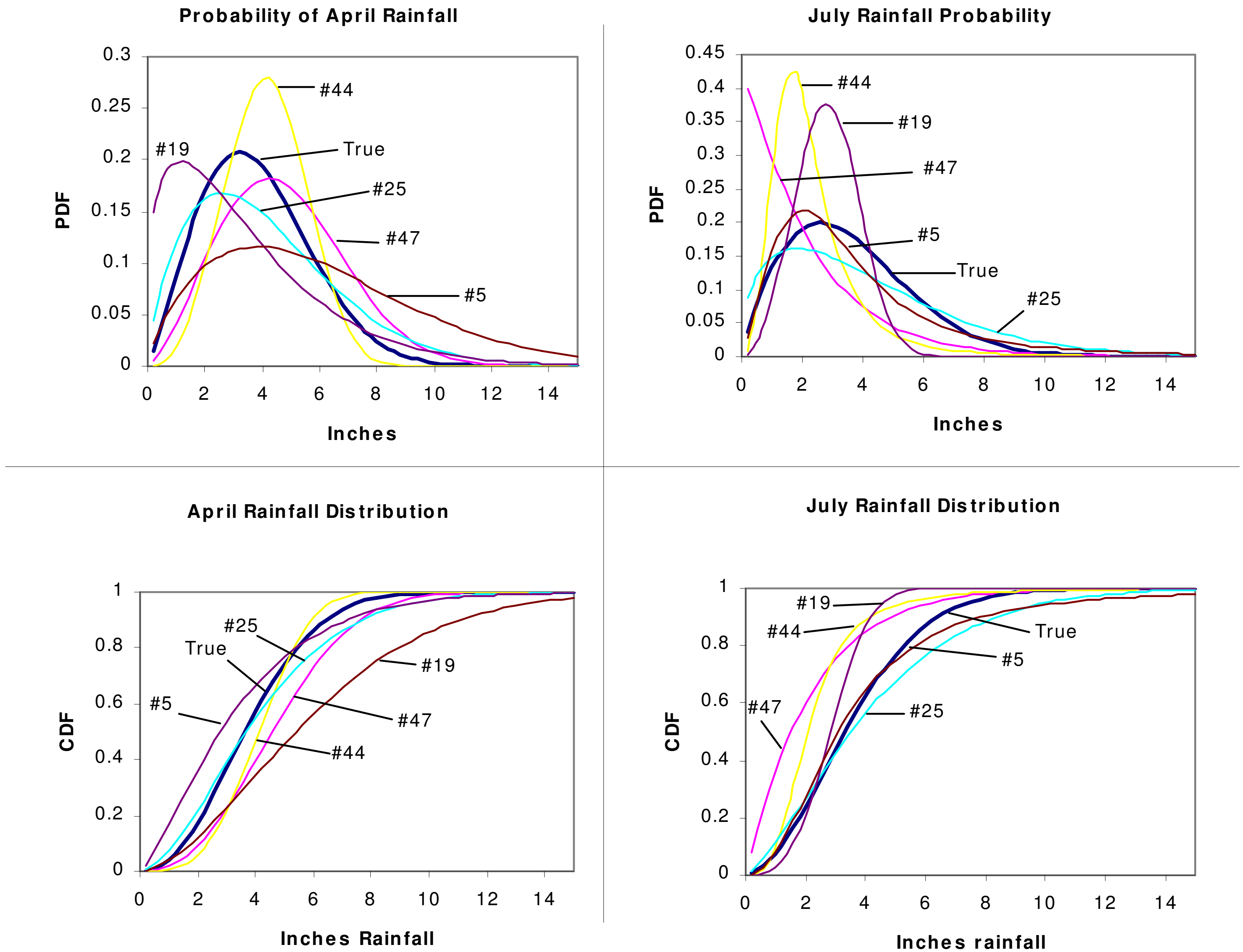


Figure 2. Calibration Functions

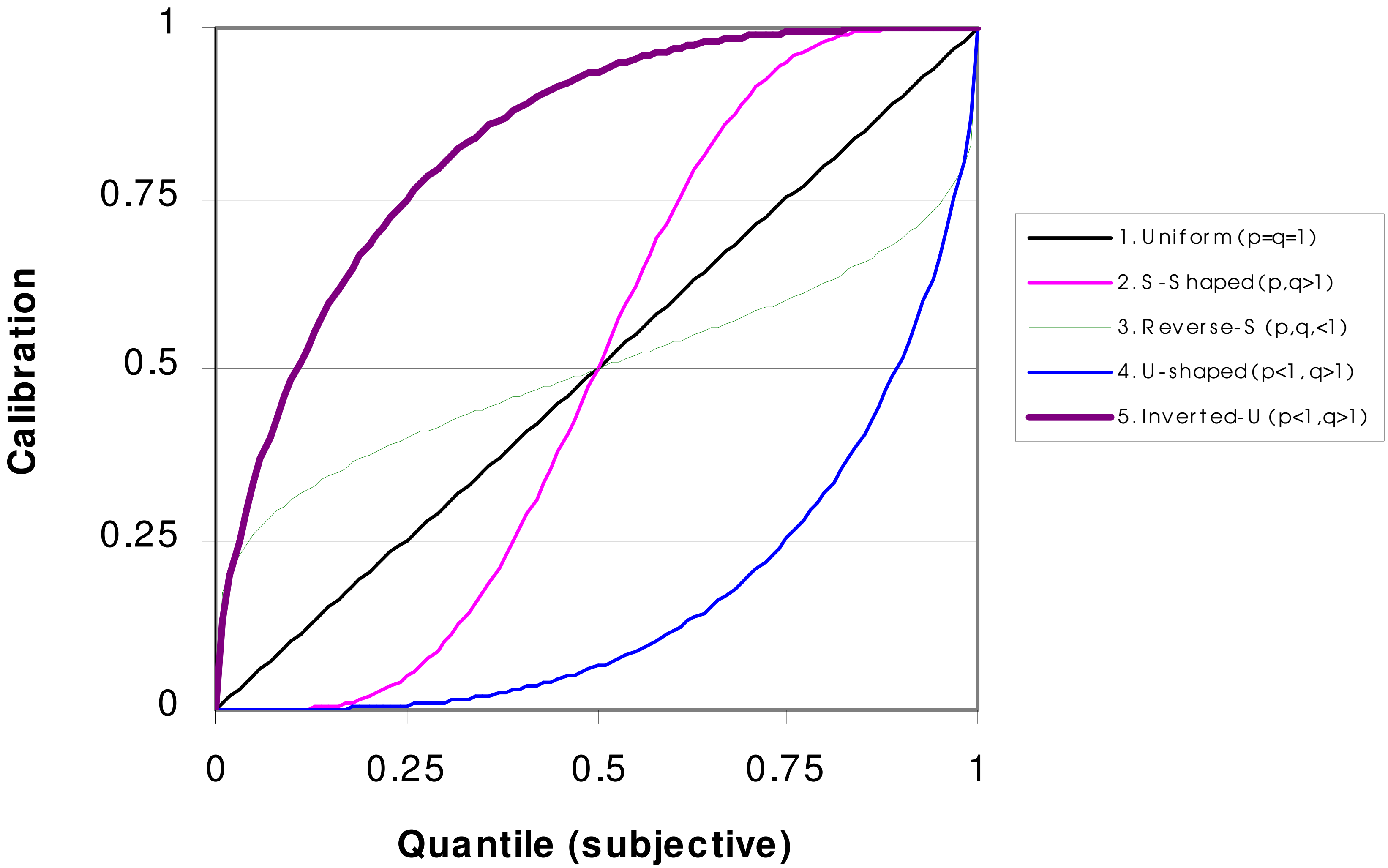


Figure 3. April excess rainfall insurance values under actual and producer probability distributions

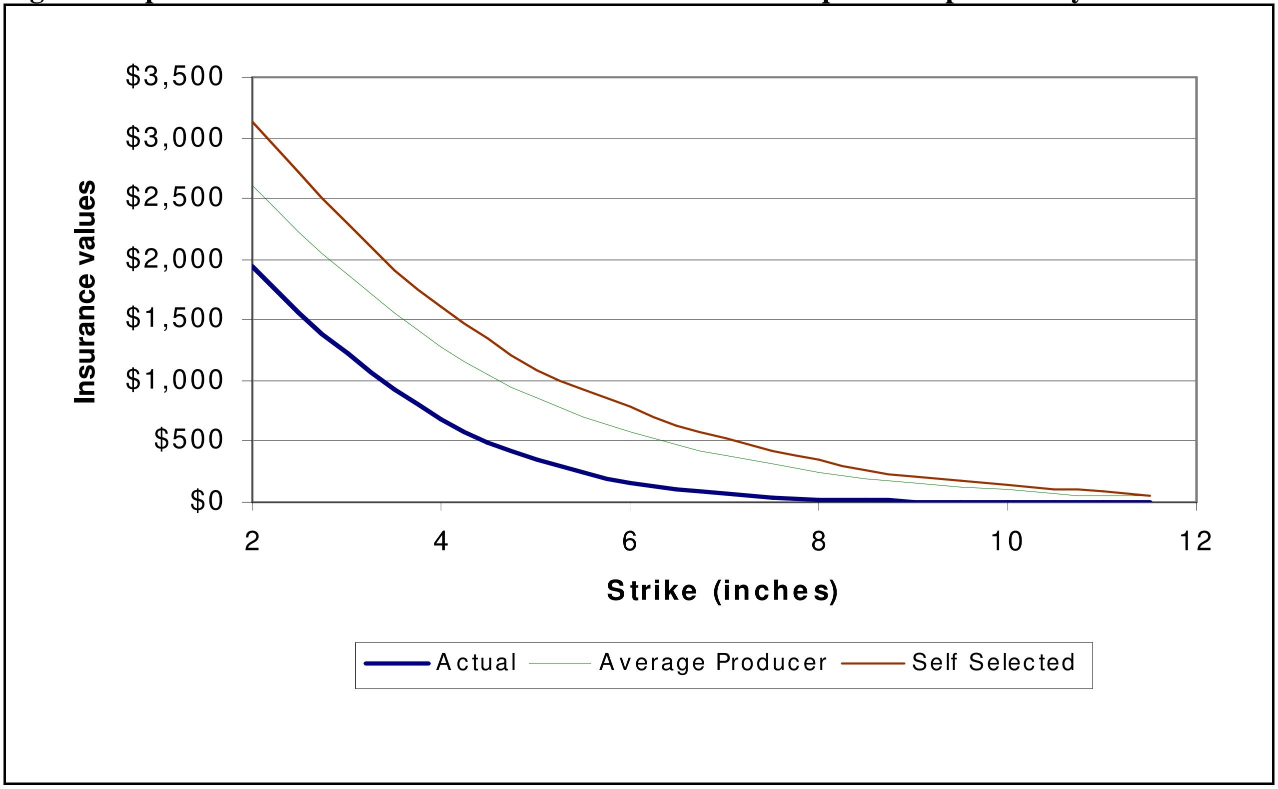
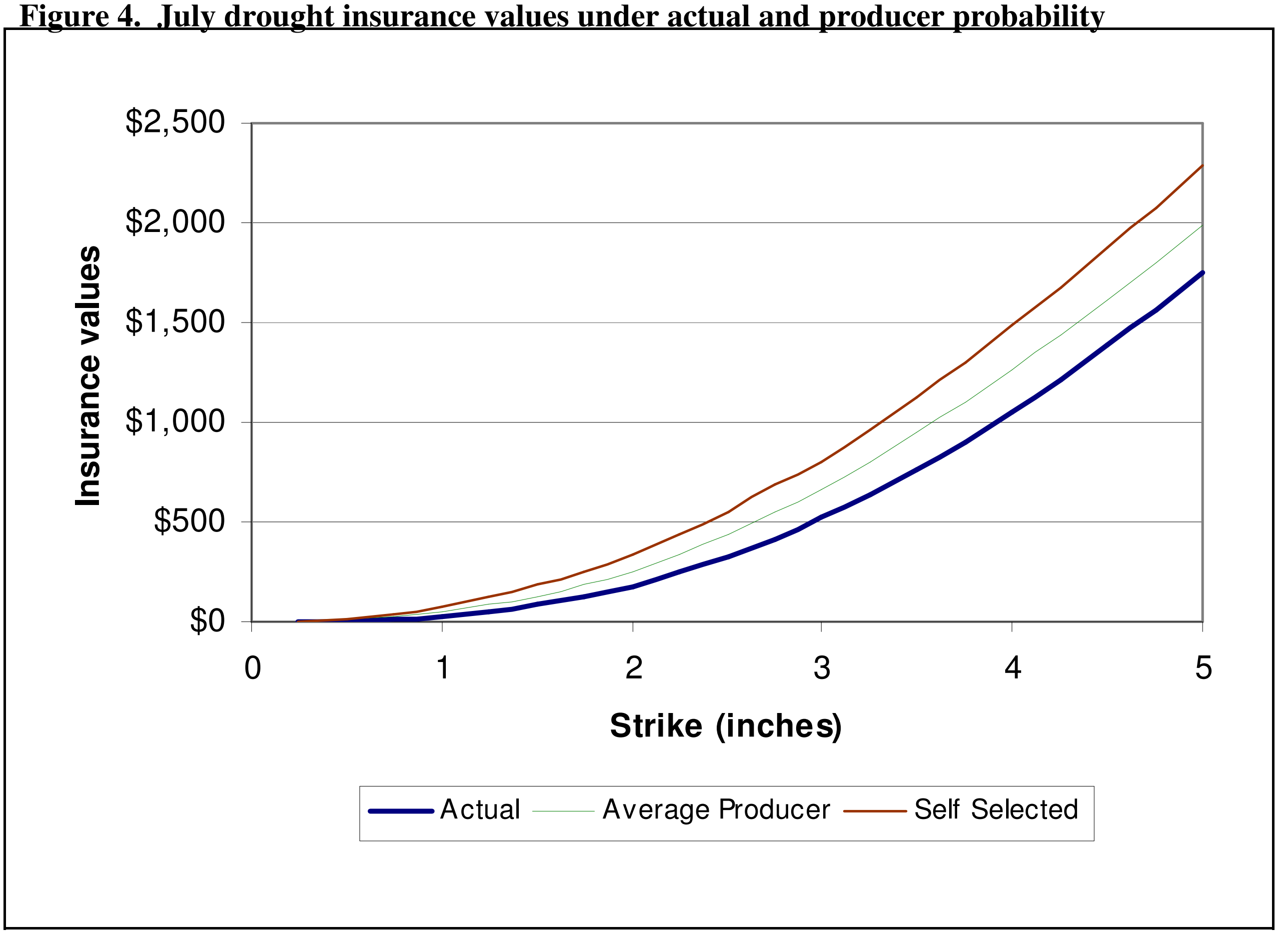


Figure 4. July drought insurance values under actual and producer probability



Footnotes:

1. A copy of the complete survey document is available upon request. While the sample is relatively small in some sense, these were all commercial scale farmers in a single weather reporting station and all participants of a recordkeeping system that signals that they have high quality financial information. Each producer provided considerable detail about their operations and beliefs. A larger sample would have necessitated loss of detail and would have required comparisons to data from more than one weather reporting station.

2. The survey was conducted during the summer of 1991 as part of a larger project examining producer beliefs. Producer subjective distributions were also recovered for commodity prices, temperature during pollination, winter precipitation, interest rates, and other variables that affect financial performance. Others have also examined non-weather expectations. For example, Eales et al. examine the congruence between producer and merchant expectations and market implied distributions of commodity prices, and find that producers have accurate means but tend to have understated variances. Likewise, Pease et. al, examine subjective beliefs about yield and find miscalibrated producers' expectations that could substantially affect insurance valuation. Kenyon likewise finds that producers have significantly miscalibrated beliefs with a tendency to overstate the probability of lower prices and understate the probability for large increases.

3. Various related parameterizations have been presented in the literature including Burr-3, Burr-12, Kappa, gamma, and Lomax versions. Mielke demonstrates the favorable performance of the Burr over the gamma but leaves other choices unranked. In this study, the Burr-12, Kappa-3, and Burr-3 parameterizations were each fitted with negligible resulting differences. The results presented herein are from the Burr-12 set of estimations only, as the other two were qualitatively identical.

4. The discussion is presented in terms of actuarial values only without the additional value that the producer would be willing to pay as a risk premium if risk averse. Likewise, insurance loading costs are not considered, but from an insurance provider's perspective, the positive misperceptions of value by producers provide a greater potential to add profit loadings to insurance contracts or cover greater actual expense loadings and should stimulate the supply of such insurance relative to a case in which producers had accurate beliefs.