SUBJECTIVE AND OBJECTIVE RISK PERCEPTIONS AND THE WILLINGNESS TO PAY FOR AGRICULTURAL INSURANCE: EVIDENCE FROM AN IN-THE-FIELD CHOICE EXPERIMENT IN RURAL CHINA.

A Thesis

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ABSTRACT

We conducted in-the-field choice experiments in China to investigate farmers' willingness to pay for crop insurance and to determine how objective and subjective beliefs affect Willingness to Pay (WTP). We deploy three variants of the choice experiment using a priming mechanism on objective and subjective beliefs plus a control. We find that the cuing frame matters in that there are distinct differences in WTP within five attributes and across variants. In terms of policy practicality our results suggest that farmers' frame of reference can affect insurance demand. We then examine whether WTP choices were determined by affective choice, dual processes and/or expected utility. In a follow-on survey we asked farmers to state minimum, typical or most likely, and maximum yields from history (objective risks) and the next-harvest future (subjective risks). These were used to construct objective and subjective probability distributions for each respondent farmers using the beta-PERT distribution. The first approach interacts choices with mean, standard deviation, and skewness about a generalized Taylor's series expansion about utility. The second interacts the certainty equivalents drawn from a logarithmic utility function. The third involves a scoring function based on the subjective-objective spread of PERT cumulative distribution functions. Results were mixed. We find that the direct expected utility approach was unsatisfactory because of over-fitting. However, with strong multicollinearity between primal choices and the certainty equivalent measures we conclude evidence of a utility -centric dual process model. However, when the dual-process analytical component was based on the cumulative distribution scoring rule, the dual process hypothesis is weakened considerably.

BIOGRAPHICAL SKETCH

Born from Beijing, China, Yinuo An has developed extreme interest in Agriculture-related fields since young. Starting from high school, she has participated in several agricultural projects, such as an experiment that collaborated with farmers and recorded their technical struggles on how to evenly apply pesticides. Those experience inspired Yinuo to study Managerial Economics at University of California, Davis, with the emphasis in Agricultural Business.

After four years at University of California, Davis, because of taking courses like Agricultural Labor, Agricultural Policy, and farm management, Yinuo An has further developed her interest in agricultural management. As a result, she continues to pursue her academic journey at Charles H. Dyson School of Applied Economics and Management at Cornell University with the Emphasis in Agricultural and Food Economics. Yinuo An has deeply motivated by the two-year study and investigated the subjective and objective risk perceptions and the willingness to pay for agricultural insurance, as her MS graduate thesis.

This summer, Yinuo An has accepted the job offer from PricewaterhouseCoopers as the research associate focusing on merge and acquisition of agriculture-related firms. She hopes to apply her accumulated knowledge to support her career path and make contribution to those agriculture-related industries.

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CHAPTER 1

INTRODUCTION

How subjective and objective beliefs affect insurance decisions is an important economic problem. Competing paradigms include the expected utility model (EUM), prospect theory, and dual-process comprising emotional (e.g. affect) and analytical processes. These approaches transcend disciplinary boundaries and are generally presented as being mutually exclusive. They may not be. In this paper we explore how objective and subjective beliefs, and objective and subjective probability distributions affect the willingness to pay (WTP) for certain attributes of crop insurance in China. In doing so, we contribute to the growing interest of applying behavioral economics to problems of agricultural insurance, while also gaining practical and policy-instructive insights into farmers' demand for insurance.

China's expanding crop insurance industry in the modern era was initiated by the First Policy Document issued in 2004. Between 2007 and 2019, China has delivered agricultural indemnities of between 112.6 billion RMB to 3.5 trillion RMB and agricultural insurance premiums have increased from 5.18 billion RMB to 68 billion RMB. Presently, China provides agricultural insurance services for over 178 million farmers covering 221 crops (China Banking and Insurance Regulatory Commission 2020).

Despite the rapid growth in crop insurance offerings in China, relatively few studies have attempted to understand the risk motives affecting farmers' uptake and participation in the program. A particularly interesting problem raised by Turvey et al. (2013) is the relationship between objective and subjective beliefs and distributions applied to the crop insurance problem. If insurers rely on objective distributions to write insurance contracts, while insureds rely on subjective distributions to determine the utility of those contracts, then behavioral frictions leading

to market disequilibrium can arise. This follows the line of reasoning in Johnson et al. (1993) that framing can create biases in probability assessment and in perception of loss which can affect insurance decisions. If farmers exhibit systematic biases in how they judge insurance contracts markets may fail to operate efficiently. Similarly, studies by Hsee and Menon (1999) and Hsee and Kunreuther (2000) assert that the affect heuristic (Slovic et al. 2002) is involved in insurance decisions and the willingness to purchase and pay for insurance is not based on objective probability assessment as the Expected Utility Theory proposes, but rather on the degree by which the insurance consoles (consolation hypothesis) the insured. This in turn is supportive of claims by Fischhoff et al. (1978) that the judgements of risk and benefits are negatively correlated. In the insurance context the contract can be perceived as being high in benefits when a payoff occurs but low in risk since the most that can be lost is the premium. On the other hand, if probability of loss is perceived as being low, the loss of premium is viewed as a high risk. At least one study, by Babcock (2015) for crop insurance in the United States provides experimental evidence of this effect.

1.1 Our Approach and Methods

How objective and subjective beliefs affect the crop insurance decision in China is the subject matter of this paper. In this paper we report in-the-field choice experiments (CE) applied to Chinese wheat farmers in Shaanxi and Shandong provinces. There were 3 randomly assigned variants of the CE. The 1st primed farmers to recall historical yields. The 2nd variant primed farmers to consider the next crop grown (wheat). The 3rd variant was a control which did not prime farmers at all. The underlying theory is that of objective utility and subjective utility, and whether farmers primed to objective beliefs and subjective beliefs would respond differently to CE attributes and willingness to pay (WTP) for these attributes. Our use of priming is well founded in the literature.

For example, the affective primacy hypothesis (Zajonc 1980; Murphy and Zajonc 1993) holds that positive and negative affective reactions can be evoked with minimal simulative inputs and virtually no cognition. The cognitive part deals with the rational assessment of probabilities presumed in the rationality of the EUH. Affective reactions refer to feelings of goodness or badness, liking or disliking, pleasure or displeasure. If decisions of insurance choice involve affect then the pathway that steers choice is through observant and non-observant cues, and it is these cues that trigger affect (Zajonc 1980). Affect is prone to adjective appeal. The crop was good or bad; or the crop will be good or bad. But in an experimental setting how the farmer feels about crop yield means or their distributions is unobservable to the researcher. By priming our CE towards objective and subjective beliefs we take a first step in this direction, and we find that priming matters. We find that farmers evaluating insurance with objective beliefs have different WTP for attributes than those primed to subjective beliefs and control. In addition, we find these WTP results to be robust to different econometric specifications that incorporate objective and subjective probabilities directly. In a short follow-on survey, we asked farmers to explicitly provide their objective and subjective beliefs about the minimum, most likely, and maximum yields with these three parameters we convert beliefs to probabilities using a beta-PERT distribution. These distributions provide mean, standard deviation and skewness measures and related probabilities that we use in robustness tests. We then test the findings against various forms of utility. The first is a Taylor's series expansion about a generalized utility function with interaction variables of objective and subjective mean, standard deviation and skewness. The second assumes a log utility with the expected utility and certainty equivalents of crop yields generated for each farmer respondent using Monte Carlo techniques. The third uses a scoring rule to measure the (stochastic) dominance of subjective probabilities over objective probabilities at

each pentile of the cumulative probability distribution. We find in two of the three robustness checks that the main CE results are robust. The generalized utility model fails because of over fitting. For the certainty equivalent and scoring rule models we find that additional farmer-specific information about probability distributions does not alter the primitive results in a meaningful way. We conclude from this analysis that the WTP measures, including that of the control, do take into account risk perceptions. These are consistent with findings in Kusev et al. (2012) who find that risk preferences are influenced by the accessibility of events in memory. As a practical matter the policy implication of our paper is that farmers' decisions to participate in crop insurance programs may well be due to their frame of mind.

CHAPTER 2

CONTEXT AND LITERATURE

2.1 Subjective Beliefs and the Insurance Decision

The real-world problem of farmers' uptake of insurance may well be due to a mismatch between the objective beliefs about historical probabilities as desired by the insurer, and the subjective beliefs of future outcomes that the insured would use to assess the qualities of the insurance contract. Anderson et al. (2014, Page 208) define subjective probabilities as those probabilities that lead an agent to choose some prospects (e.g. insurance) over others (e.g. no insurance) when outcomes depend upon events that are not presently realized. Earlier interpretations by Knight (1921) define objective risk as unalterable, while subjective risks, or uncertainty, are alterable and malleable Willett (1951) states that subjective uncertainty is a faithful interpretation of events in the external world. Pfeffer (1956) adds that risk is a combination of hazards measured by probability while uncertainty is measured by a degree of belief: Risk is a state of the world, but uncertainty is a state of the mind, (c.f. Houston 1964).

This mindful approach has evolved into a science of risk perceptions by Fischhoff et al. (1977), Camerer and Lovallo (1999) and others. History might well represent the subjective future, but for a variety of reasons subjective risks do not necessarily imply representativeness (Tversky and Kahneman 1983, 1986; Kahneman and Tversky 1972, 1979). In many experimental setups, all respondents are provided with identical objective probabilities of outcomes. Yet, even with perfect foresight of probabilistic outcomes, because the actual outcomes are as yet unknown, respondents gamble and assign subjective probabilities to make their choices even when under the rules gaming the system is impossible. For example, they may show greater enthusiasm for lotteries with a large potential payoff and less enthusiasm for a lottery with a lower potential

payoff, even when the objective mean of the former is lower than that of the latter. Anderson et al. (2014) warn us, however, that such choices are more likely derived from risk attitudes formed by the curvature of utility functions than subjective probabilities directly. They then show through a number of experiments how knowledge about risk attitudes can be used to derive subjective probabilities. In one such experiment Antoniou et al. (2017) explore the strength-weight hypothesis proposed by Griffin and Tversky (1992). Griffin and Tversky hypothesize that decision makers tend to focus on the strength of a signal, rather than its weight or relevance. A drought or other extreme shock (high strength) with positive or negative affect can lead to a form of hysteresis, or path dependency in conscience, even though the shock or event was overstated in real importance (low weight). Judgements drawn under a strength-weight paradigm can lead to overconfidence when strength is high and weight is low, and under-confidence when strength is low, and weight is high. It seems naturally plausible that these judgments can create filtration rules that can cause a realignment of subjective probabilities from the objective truth. This, in turn, can alter the weightings that farmers place on certain attributes of crop insurance products, or at least those such as premium, coverage and indemnity that deal with underlying probabilities. In our paper we cannot evaluate differences in objective and subjective probabilities within the strength-weight hypothesis, but experimental research such as Antoniou et al. (2017) does find evidence that perceived events are more likely when the available evidence has high strength and low weight

Our focus on subjective beliefs in an in-the-field choice experiment on insurance demand draws from findings in Turvey et al. (2013) who identify several typologies in objective and subjective probability distributions that suggest that farmers recalibrate probabilities, and that this calibration can affect insurance demand. Typologies are mixed suggesting a representativeness heuristic that leads to under or over-confidence in some parts of the population. Overconfidence

can refer to an overestimation of one's ability or performance relative to others, self-importance, or an excessive certainty about the accuracy of beliefs (Harrison and Swarthout 2019). While discrepancies in objective and subjective risk, and degrees of confidence, have been discussed in the agricultural economics literature, empirical works are very rare. Umarov and Sherrick test farmer overconfidence specifically and in the context of crop insurance. Overconfidence can result from miscalibration (Lichtenstein et al 1982), optimism, and the 'better than average' effect (Svenson 1981; Gervais et al. 2002). Umarov and Sherrick (2005) find that farmers tend to be overconfident. When subjective beliefs dominate objective beliefs Umarov and Sherrick argue that not only would the willingness to pay for insurance decline, but so too will be the imperative that insurance is required at all. They find that only 6-7% of farmers admitted yields lower than the (detrended) county average, and only 15-15% reported a higher variability. Moreover, they find a mix of calibration curves which map (cross-tabulate) objective and subjective crop yield probability distributions. They found multiple over-under confident typologies across mean, variance and skewness as was also found for Chinese farmers (Turvey et al. 2013), Buzby et al. (1994) investigated objective and subjective risks of Kentucky farmers and found that an inclination to overestimate yield and underestimate risk. Turvey et al. (2013) studied subjective and objective risks for Chinese farmers and found that 82.3% had forward corn yield expectations greater than their historical recall, and 71.63% perceived future risks to be lower than their historical recall, and that these subjective beliefs were determinative in driving insurance demand. Pease et al. (1993), Sherrick (2002) and Bessler (1980) make similar assertions, but in a direct test, Umarov and Sherrick found no relationship between miscalibration and insurance demand. Ramirez and Carpio (2012) similarly find a disconnect between the objective measures used to calculate crop insurance premiums and how farmers judged those premiums. In the USA Gardner

and Kramer (1986) and Glauber (2004) argue that farmers have required subsidies to encourage enrollment in crop insurance, and this may well be due to misaligned perceptions of objective and subjective risks. Similar results have been found in studies on the heterogeneity of risk by Spinnewijn (2012) outside of agriculture.

Drawing on Eckles and Wise (2013), Babcock (2015) uses a representative farmer model to examine revenue assurance in the USA using prospect theory (Kahneman and Tversky 1979, 1992). As with Eckles and Wise (2013), Babcock observed that many USA farmers do not buy the maximum amount of insurance available but will elect lower coverage levels. Prospect theory probability weights, often referred to as decision weights, are simply another measure of risk preference, and are not designed to model an individual's subjective beliefs about risk. In this theory what is observed subjectively is not necessarily a revision of probabilities but the judgment and weighting of known outcomes. Assuming loss aversion and the expected utility theory (EUT) farmers would place greater weight on economic losses than economic gains and would therefore, at least in theory, have greater demand for crop insurance and with higher coverage levels. Babcock does not find support for this model. Instead, he concludes that observed behavior for revenue protection insurance is more akin to an investment choice independent of underlying risks. More recently, Dalhaus et al (2020) state that the cumulative prospect theory, applied to adjusted crop insurance according to farmers' preferences, is more consistent with farmers' willingness to pay. In this framework, high premiums without an offsetting indemnity is weighted as a loss which then diminishes demand. We have previously identified Babcock's (2015) conclusions as providing evidence of affective judgements about negative correlation between risk and benefits as proposed by Fischhoff et al (1978). Although we do not advance prospect theory in this paper,

a similar observation might result if the farmer weighs crop insurance decisions based on overly optimistic subjective probabilities.

There are many approaches to measuring subjective probability distributions using scoring rules. A scoring rule asks the respondent to make a report about their beliefs relative to a specific metric, and this metric may be a series of bins or ranges along the domain of an outcome variable (e.g. crop yields). More complex scoring rules have been deployed in incentive compatible experimental work. Andersen et al. (2014) describe linear and quadratic scoring rules in experiments that provide monetary rewards for how close a subjective belief about how an outcome matches inferences obtained from a presentation of an objective distribution. They make clear distinctions between subjective beliefs and subjective probabilities, but then show through a series of experiments how subjective probabilities can be elicited through specification of a utility function (see also Harrison et al. 2014). Agricultural examples of scoring rules are rarer because that brand of economics generally applies tools to famer populations which tend to be more difficult to reach. Umarov and Sherrick use historical county level yields to define objective distributions based on a Weibull distribution. Subjective probabilities were obtained by providing farmers with yield ranges and asking them to assign probabilities to a yield in each range and then compared these assignments to the objective distribution measure. Agricultural development economists often require in-the-field studies in remote agricultural regions where important discussions about how subjective probabilities are measured and how they feed into household decisions, including insurance (Delavande et al. 2011). Traditional measures involve asking about beliefs in questionnaires using a Likert scale, or asking farmers to allocate trinkets of some sort into squares or buckets depending upon how they believe, or the weights they place on, a future event occurring.

In Delevande et al.'s (2011) review they find some evidence that indeed there is a casual relationship between these subjective probability assessments and decision outcomes. Lybbert et al. (2007), for example, point out that in remote areas objective probabilities are missing in reality, and any decision making by (in their case pastoralists in Kenya) farmers must be based on subjective beliefs about the future. To convert these beliefs to probabilities they ask the pastoralists to place stones to weigh the likelihoods that the next season would bring about above normal, normal and below normal precipitation, with reasonable results. Dominitz and Manski (1997) (see also Manski, 2004) ask respondents to identify minimum and maximum income expectations in the following year and fill these points with quartile values that are then fitted to a lognormal distribution for which mean, standard deviation and mode can be measured. Kong et al. (2011) used the 3-parameter PERT distribution to investigate weather insurance demand in China, while Turvey et al. (2013) used the PERT distribution to investigate objective and subjective risks as they relate to Chinese crop insurance. Again, the applications of behavioral concepts and risk perceptions to agricultural decision theory and insurance are limited.

2.2 Conceptual Framework

To place the above in perspective we start with Figures 1 and 2 that were drawn from our sample of Chinese wheat farmers. Keep in mind that we did not prime farmer-respondents on these objective/subjective probability distributions directly, but only in reference to objective/subjective beliefs about historical/past years yields and future yields. The six panels of Figure 1 illustrate a number of typologies observed for 6 different farmers. The probability distributions are PERT distributions which are convenient because they are bounded distributions requiring the farmer to identify only the minimum, most likely and maximum yields. In a short survey attached to the CE we asked farmers to consider a future harvest and what they believe would be the minimum, most

likely, and maximum yields in a local measure of jin/mou (approximately 500 grams per 1/6th of an acre). This was followed by asking farmers to recall the worst, best and typical yields they had experienced. As the former is forward looking, we refer to these as subjective beliefs, and since the latter was historic in nature, we refer to it as objective beliefs. These beliefs form the boundaries for subjective and objective probability distributions as presented. Our interest is in determining how subjective versus objective risks affect insurance decisions. In taking this approach we individualize risk perceptions.

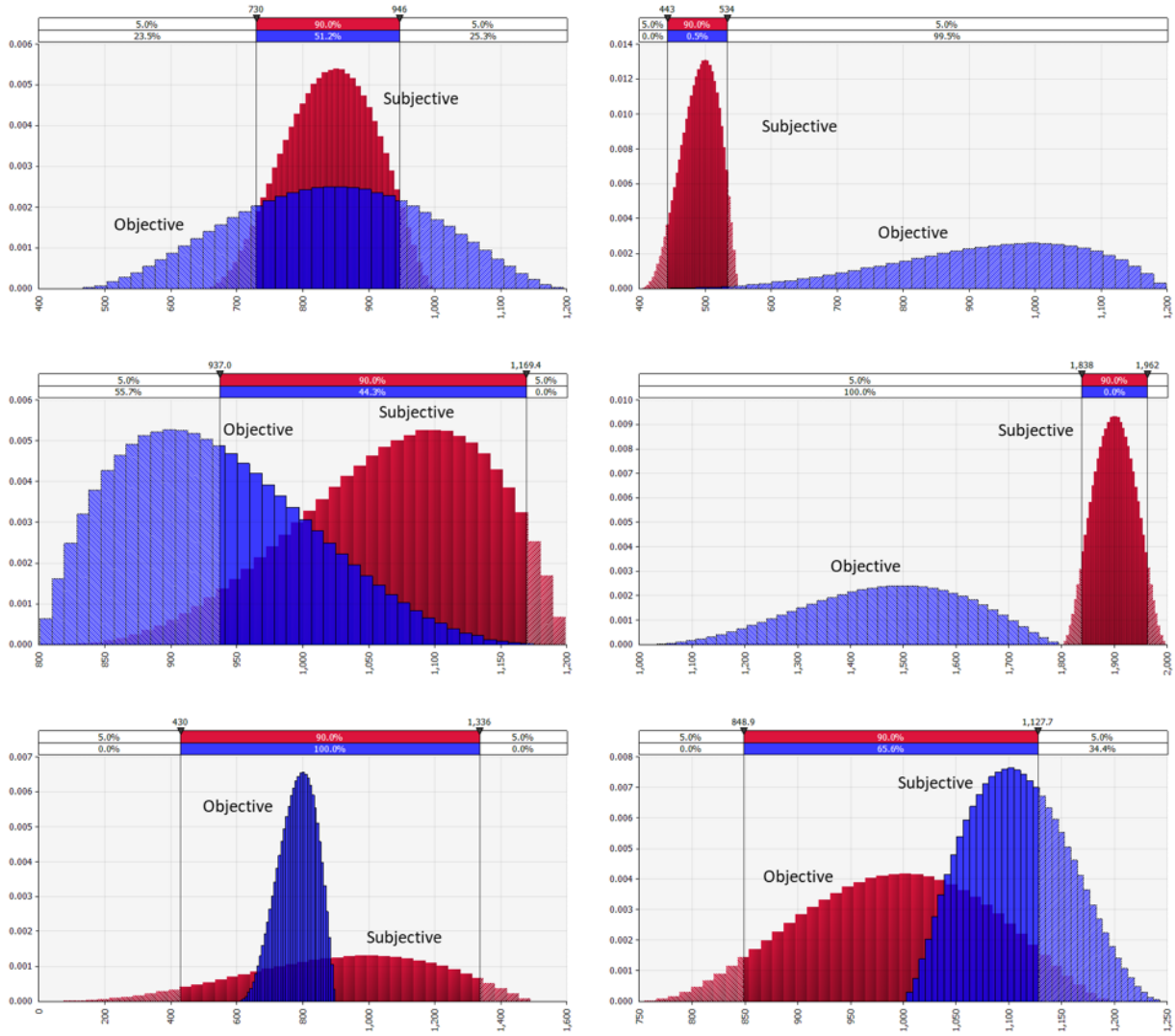

Figure 1. Selected PERT distributions

Top Left: Approximately same mode, with subjective variance lower than objective mode, Top Right: Pessimistic subjective, Mean subjective below objective but with lower variance. Center Left: Subjective distribution mode higher than objective mode, with negative vs positive skew. Center Right: Optimistic. Subjective mode greater than objective mode, with lower variance. Bottom Left: Subjective mode, greater than objective mode, but with higher variance. Bottom Right: Subjective mode greater than objective mode, with lower variance.

Although typologies can be generalized between objective and subjective risks, for example optimistic or pessimistic, higher variance or lower variance, greater skew or lower skew each respondent is individualistic and generally unique. So too are the respondent choices to the Choice experiment and our goal is to determine whether the willingness to pay (WTP) across the three primed variants are endogenously determined by risk perceptions. It allows us to examine how strong Zajonc's (1980) 'affective primacy hypothesis' which asserts that positive and negative affective reactions can be evoked with minimal simulative input (e.g. our priming cues across variants) and virtually no cognitive processes. The conjuring of the probability distributions in Figure 1 requires some cognitive processing, but whether these have influence in the WTP for insurance is a different matter which we can examine.

More broadly, the three panels in Figure 2 illustrate the mean, standard deviation and skewness scatterplots from our objective and subjective measures. The top panel shows a reasonably strong consistency in objective versus subjective mean yields, but the relationship between objective and subjective standard deviations and skewness is very weak. These latter observations bring into question the Knightian conclusion that subjective and objective risks ought to converge. From a behavioral point of view these can affect insurance outcomes. The insurer, for example, will seek to determine the actuarial rate from the objective-historic measures. The insured, however, will consider insurance in light of subjective beliefs about future risks. These future risks may be conditioned by objective risk, at least in terms of expected yields, but the conditioning is much weaker when it comes to standard deviation and skewness.

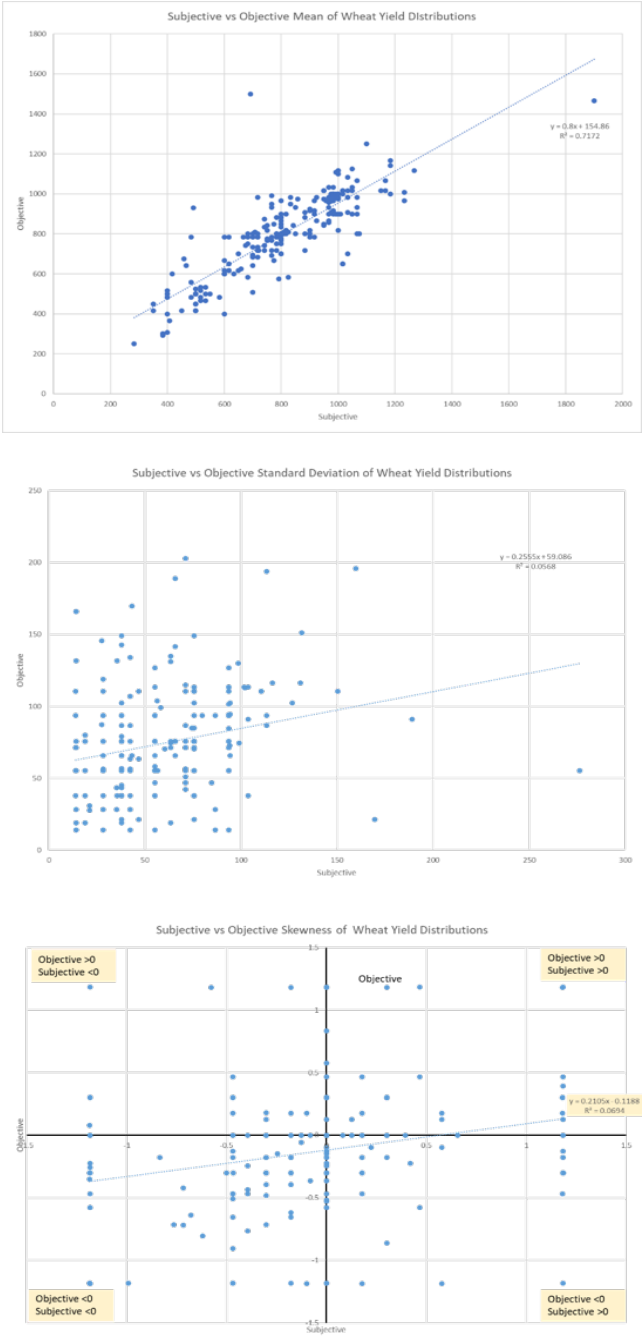

Figure 2. Relationships between Subjective and Objective Risks

Top: Comparison of Objective and Subjective mean yields. Center: Comparison of Objective and Subjective standard deviations. Bottom: Comparison of Objective and Subjective skewness.

CHAPTER 3

METHODS

3.1 Choice Experiment

We use in-the-field choice experiments to derive willingness to pay (WTP) for attributes on agricultural insurance. Choice experiments have been used in a number of agricultural settings including transport studies, environmental valuation, and food choices (Adamowicz, et al. 1998; Jayne et al. 1996; Unterschultz et al. 1998). In the choice experiment, respondents make decisions in choice scenarios that involve a discrete number of alternatives. Each alternative is described by levels of a set of predefined attributes. The tradeoff between different crop insurance alternatives can therefore be analyzed through the choices that farmers make. Furthermore, if there is a price-related attribute in the experiment design, the willingness to pay (WTP) for other attributes can be estimated (McFadden's 1973, 2001).

Our choice experiments are based on D-Optimal, 6-block design, with 9 cards per block and 3 choices per card. We do not provide an opt-out option. Each card consists of five attributes as listed in Table 1. With the overall objective of determining whether objective or subjective beliefs can affect insurance demand and the WTP for certain insurance attributes we randomized among three variants by priming the farmer to consider the minimum, maximum and most likely yields from their historical recall (objective beliefs) or in relation to the next typical wheat harvest (subjective beliefs). The third variant, a control, used no priming at all.

Table 1 Attributes and Levels

Attribute	Description	Unit	Level
Claim starting point	Minimum damage percentage to get insurance compensation. For example, if the damaged area is 20% or greater than 20% of a farmer's planting area, this farmer will get compensation from the insurance company.	Percentage (%)	10; 15; 20; 25; 30
Premium	Price of farmers need to pay to buy certain insurance products.	RMB per Mou (¥ / Mou)	1; 5; 10; 15
Indemnity	Compensation that farmers will get from insurance companies after claiming the damage.	RMB per Mou (¥ / Mou)	300; 400; 500; 600
Type of insurance	Private or government owned insurance	/	Yes; No
Loan Option	Whether the insurance can be used as loan collaterals.	/	Yes; No

Our attributes and terminology are based on terms used in Chinese crop insurance contracts and would be familiar to most farmers. The claim starting point is equivalent to coverage ratio as applied in the United States, and elsewhere, and captures the minimum damage ratio requirement of an insurance product so that farmers can get compensation. A claim starting point of 15% is equivalent to 85% coverage in the USA. We used 4 levels for crop insurance premiums. Insurance on grain is the most dominant insurance type in China, covering 70 percent of farmers. Premiums for grains (rice, wheat, and corn) ranged from 15 RMB/mu to 36 RMB/mu but are heavily subsidized. The subsidized premiums ranged from 3 RMB/mu to 7.2 RMB/mu. Our range from 1 RMB/mu to 15 RMB/mu includes an even greater subsidy at the lower end, and zero subsidy at the higher end (Anhua Agricultural Insurance 2019).

Table 2 Premium of Grain-related Insurance

Category	Premium (RMB/Mou)	Premium after Subsidized (RMB/Mou)
Wheat	15 ~ 27.5	3 ~ 5.5
Corn	15 ~ 36	3 ~ 7.2
Rice	17.5 ~ 32	3.5 ~ 6.4

Indemnities are based on public crop insurance contracts (Anhua Agricultural Insurance 2019) as the reference. The indemnity of wheat and rice is considered to be 240 to 600 RMB per Mu (1/6th of an acre), and the indemnity of corn is around 350 RMB per Mu. As a result, we distributed the indemnity level from 300 to 600 RMB per Mu. We include a provider attribute. Whether the insurance provider is government-owned or private-owned is an important attribute. Chinese farmers are suspicious of private insurers and might have a preference for publicly provided insurance. Experimental work by Harrison and Ng (2018) has shown that insurance non-performance can impact insurance demand and Wang et al. (2020) in a series of choice experiments in China show that farmers' past experience has a strong influence on their WTP for crop insurance. Chinese agricultural insurance market currently provides farmers with two major categories of agricultural insurance, which is our fourth attribute. One as government-owned agricultural insurance, the other as private-owned agricultural insurance, also called commercial agricultural insurance. Government-owned agricultural insurance is usually a government-led or government-established agricultural insurance company. Government-owned agricultural insurance takes into account the benefits of the whole society and provides farmers with different levels of subsidies on premiums. Government-owned agricultural insurance, however, lacks flexibility by providing a single rate for a single coverage level and indemnity structure. Commercial agricultural insurance on the other hand are fully market-oriented operations with the

goal of maximizing profits. Farmers can choose the premium within the scope of insurable benefits, and even the indemnity can be negotiated.

The fifth attribute is whether the insurance can be used as loan collateral. This is a fresh but well-generalized concept of agricultural insurance in China. The Chinese government has initiated a new loan collateral option that links credit to agricultural insurance. In 2010, the China Banking and Insurance Regulatory Commission released an official document named *Opinions on Strengthening the Cooperation between Agriculture-related Credit and Agriculture-related Insurance*. The document encouraged the cooperation between banks and agricultural insurance companies with favorable loan rates and faster loan application to farmers with agricultural insurance. In other words, this agricultural insurance contract could be used as loan collateral.

We presented the choices under the block design using cards with images and descriptions to make the attributes easier to understand. The image in Table 3 represents 1 card in a sequence of 9 cards/blocks presented to the farmer. Each farmer was randomly assigned to 1 of 6 blocks. The non-orthogonal block design and reporting schedule was computed using JMP software. Each of the 3 variants (objective beliefs, subjective beliefs, control) used identical block designs, except the preamble read to each respondent differed.

Table 3 The Example of Choice Card

	Insurance A	Insurance B	Insurance C
Claim Starting Point	20%	15%	10%
Crop Indemnity (RMB/Mu)	300	400	500
Crop Premium (RMB/Mu)	10	5	1
Types of Insurance	Commercial Insurance	Commercial Insurance	Government-owned Insurance
Loan Collateral	No (Cannot be used as collateral)	Yes (Can be used as collateral)	No (Cannot be used as collateral)
Your Choice			

3.2 Experiment Design

Since we are distinguishing farmers between objective and subjective risk, we randomly divide farmers into three groups: objective group, subjective group, and control group by applying preambles. The reason why we do not apply objective and subjective risk to one farmer is because of the anchoring bias, the common human tendency to rely too heavily, or "anchor," on one trait or piece of information when making decisions (Cervone 1990). Preambles are reinforced every time by our researchers before farmers make each choice. The preamble of the objective group is “try to choose one favorite insurance product considering your typical historical wheat yield.” Subjective group is classified by the preamble “try to choose one favorite insurance product based on your prediction of your most likely wheat yield next season.” Control group is in absence of preamble. After making choices for all 9 cards, farmers were interviewed and completed a short

survey to capture the personal information, such as yield, of each farmer. Each farmer was paid 30 RMB for participating.

To satisfy the rank condition we elected a protocol commonly used in choice experiments (Orme 1998; Johnson and Orme 2003; and Rose and Bliemer 2013) to calculate the minimum sample size:

$$N \geq 500(\frac{l^*}{S * J})$$

Here, S is the number of choice tasks presented to each respondent (9, in our case), J is the number of alternatives per choice task (3 in our case), and l^* is the largest number of levels of any of the attributes (5 for each choice). The rank condition is satisfied for N=93. Our original sample included 144 farmers each from Shaanxi and Shandong and 48 from Zhejiang. We dropped the Zhejiang sample because not enough farmers grew wheat, and for consistency only included wheat farmers from Shaanxi and Shandong. Our final sample was 241 farmers including 109 from Shaanxi and 132 from Shandong. The timing of our experiment was October and November 2019 which followed the corn harvest and preceded the wheat harvest. Most farmers who grew wheat, also grew corn in a double-crop rotation.

3.3 Conditional Logit vs. Mixed Logit

By convention we apply both Conditional and Mixed logit models. The conditional Logit model assumes that farmers have homogeneous preferences (i.e. WTP measures are the same for all farmers) while the mixed Logit model assumes that farmers have heterogeneous preferences (i.e. WTP measures are mixed across respondents. With each farmer responding to 9 cards the total sample for 241 farmers is N = 2,169. As ours is a conventional application of these models we refer the reader to Mcfadden (1973), Train (2009), McFadden, and Tye, & Train (1977) for

econometric details. The willingness to pay can also be calculated by the Conditional Logit and the Mixed Logit model (Train 2009), which can offer us a more direct observation on sample preferences on various attributes over our choice experiment, $WTP = -\frac{\beta_n}{\beta_p}$ where β_p is the coefficient for price-related attributes.

CHAPTER 4

RESULTS

4.1 Socio-demographic characteristics in the sample

Most farmers interviewed were over 50 with a household size rounded to 5. Land use rights held by farm households were approximately 7.63 Mou (1.27 acres) and experience in farming was approximately 34 years. Farmers we interviewed were approximately 44% men and 56% women. On average about 2.15 family members were involved in agriculture while 2.15 worked for day wages off-farm. Educational levels were low with the highest academic achievement being between middle school and high school, and the household leaders were evenly distributed as well. The average education level for farmers is between middle school and high school. Average income from farm and non-farm sources was 19,627 RMB/year or about $2,761 USD. Personal characteristics are similar between objective and subjective groups except for agricultural income. Agricultural income for farmers under objective group is higher than subjective and control group, but overall net profit is similar.

Table 4 Descriptive Statistics

Variable	Unit	Objective (N = 69)		Subjective (N = 85)		Control (N = 87)		Total (N = 241)	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Gender	1= Men, 0 =Women	0.55	0.5	0.41	0.5	0.39	0.49	0.44	0.5
Age	Years	56.86	12.22	54.15	12.83	55.69	10.78	55.48	11.95
Household Size	People	4.48	1.97	4.8	1.53	4.82	1.63	4.71	1.7
Agricultural Labor	People	2.33	1.15	2.19	1.1	1.98	0.83	2.15	1.03
Day Labor	People	1.22	1.06	1.33	1.08	1.56	0.92	1.38	1.03
Household Leader	1 = Yes, 0 = No	0.75	0.43	0.56	0.52	0.62	0.55	0.64	0.51
Education Level*		2.57	0.99	2.36	1.12	2.28	1	2.39	1.04
Farming Years	Years	35.43	14.75	33.29	15.53	33.86	13.21	34.11	14.47
Lands Owned	Mu	9.47	6.68	7.58	8.43	6.23	3.8	7.63	6.66
Agricultural Income	Yuan	16,314	17,159	8,730	10,548	7,638	11,768	10,507.	13,630
on-agricultural Income	Yuan	30,772	33,221	29,993	31,9823	46,399	30,753	36,1615	32,699
Net Profit	Yuan	13,831	40,390	16,224	31,580	27,639	27,183	19,627	33,401

*0=Never Went to School, 1=At least elementary school, 2=At least middle school , 3=At least high school , 4=Some University or college, 5=Completed College or University

4.2 Logit Results

The most significant finding, and we believe the main contribution of this paper, is that when primed to think only of historical risk, subjective risk, or no risk we find substantial differences across typologies. The base conditional and mixed Logit results for objective, subjective and control groups are provided in Tables 5 and 6. Overall, we find strong consistency between the conditional and mixed logit models. Wang et al. (2020) found considerable heterogeneity in their choice experiments in Northern China. The differences in parameter estimates we observe in our two models, while not exact across the three variants, are not so great that we can conclude strong heterogeneity in the demand for crop insurance in China. In other words, while we find significant disparities between variants, when each is compared between the conditional and mixed Logit models, the variants' coefficients are quite consistent. This suggests that while respondents have distinctive demand curves across variants, there is not a great disparity in the agricultural insurance demand curves. within each variant.

Our main purpose, besides testing which attribute is the most important, is to test whether objective belief and subjective belief have a different impact on farmers' preference on crop insurance. Comparing variants based on objective and subjective risk, farmers in the subjective risk group tend to be less sensitive on claim starting point and premium, but more sensitive on indemnity than farmers in the objective risk group. Farmers in the subjective group are more likely to choose insurance than farmers under objective risk even if the claim starting point and insurance premium went up because they are considering that they will not need the crop insurance product next year since they tend to believe there is no serious yield damage in the future they predicted. For one unit in increased crop indemnity, because of their optimistic perception on yield, farmers in a subjective risk group will have higher willingness to purchase the insurance products

compared to respondents in the objective group, meaning that they are focused mainly on the payout rather than the price and criteria of a certain crop insurance product.

Higher claim starting point is more valuable for the objective group (B=-2.993) than the subjective group (B=-1.524) and the control (B=-1.263). We had thought that if the subjective group was overconfident then they would have less of a preference for higher coverage than the control group. However, as will be discussed in the following section we find that only 44% of farmers are overconfident, and 56% are under-confident. So, in this respect the result is not surprising. We do however find this ranking for the insurance premium. We find the objective group more sensitive to insurance premiums (B=-0.05) than the control group (B=-0.0406) and the subjective group (B=-0.0406). These results confirm a downward sloping demand curve with the greater disutility from higher premiums being the objective group. We find that utility increases with the loss indemnity and this is greater for the subjective grouping (B=0.0036) than the objective group (B=0.0029) and control (B=0.0028). All three variants show a preference for government run vs privately run insurance, with the objective group having greater preference (B=0.701) than the objective group (B=0.639) or control (B=0.553). We anticipated that these would be positive. Finally, we find mixed results for linked credit. Only the subjective group had a significant coefficient (B=0.334) and this is difficult to explain. One possibility is that with an almost equal proportion of farmers being overconfident as under-confident at least some farmers may engage in risk-balancing, that is with a decrease in business risk from insurance, they are willing to take on greater financial risk. Evidence of risk balancing along these lines has been documented in Turvey and Kong (2009) and Babcock (2015).

Table 5 Conditional Logit Results

Conditional Logit	Objective	Subjective	Control	Total
claim starting point	-2.993***	-1.524**	-1.263**	-1.836***
crop premium	-0.0500***	-0.0275***	-0.0406***	-0.0383***
crop indemnity	0.00285***	0.00355***	0.00277***	0.00305***
types of insurance	0.639***	0.701***	0.553***	0.626***
loan option	0.0395	0.334***	-0.0105	0.122**
Observations	1,863	2,295	2,349	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 Mixed Logit Results

Mixed Logit	Objective		Subjective		Control		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
claim starting point	-5.828***	8.682***	-2.762**	-6.834***	-1.944**	1.343	-2.933***	-5.738***
crop premium	-0.0912***	0.122***	-0.0454***	0.0683***	-0.0593***	0.0643***	-0.0630***	0.0835***
crop indemnity	0.00593***	-0.00464***	0.00499***	-0.00621***	0.00340***	0.00441***	0.00434***	0.00553***
types of insurance	0.639***	1.411***	1.075***	1.400***	0.619***	1.240***	0.882***	1.362***
loan option	0.0745	1.525***	0.395***	0.427**	0.00898	0.739***	0.167*	0.848***
Observations	1,863	1,863	2,295	2,295	2,349	2,349	6,507	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.3 Willingness to Pay

Our conclusion that our sample of farmers were more homogenous, then heterogenous in their insurance preferences is clearer in the WTP estimates in Table 7. The WTP measures are obtained by dividing the estimated coefficients in Tables 5 and 6 by the negative of the coefficient of the premium attribute. The unit measurement is RMB. It can be seen that the differences between the two models are trivial, and that the preponderance of homogeneity is preserved across variants.

The claim starting point is referenced in terms of minimum damage requirement for the crop insurance. This appears to be the most important attribute in crop insurance demand. An increase in 5% (a decrease in coverage by 5%) decreases the demand by 59.86 (or 11.97 RMB for 1%) for the objective variant and 55.42 for the subjective variant. In comparison the control decreases by a substantially lower 31.11 (or 6.22 RMB for 1%).

The subjective variant places more value on higher indemnity (WTP=0.13 RMB/100 RMB) which is more than twice as much as the objective variant (WTP=0.06). The preferences of the control (WTP=0.07) is similar to that of the objective variant and nearly half that of the subjective variant.

Likewise, we find that the subjective variant has a greater WTP (25.49) for public provision of crop insurance, which suggests that they place far more value on the implicit guarantee of payment that comes along with public vs private insurance. This attribute is still important for the objective variant (WTP= 12.78 RMB) and control (WTP=13.62) but only by about half as much.

Finally, the WTP for a linked-credit option is not significant for the objective variant and control but is substantial for the subjective variant (WTP = 12.15 RMB). In other words, farmers under the subjective variant would be willing to pay an additional 12.15 RMB for the option of linking the insurance to agricultural credit.

Table 7 Willingness to Pay[1]

	Objective		**Subjective**		**Control**		**Total**	
	CL	ML	CL	ML	CL	ML	CL	ML
claim starting point	-59.86	-63.90	-55.42	-60.84	-31.11	-32.78	-47.94	-46.56
crop indemnity	0.06	0.07	0.13	0.11	0.07	0.06	0.08	0.07
types of insurance	12.78	7.01	25.49	23.68	13.62	10.44	16.34	14
loan option	0.79	0.82	12.15	8.70	-0.26	0.15	3.19	10.16

What can we conclude from these results? The first conclusion is that by priming farmers to anchor on future versus historical risks appears to matter. With the exception of the claim starting point the preferences of the objective variant is reasonably close to the preferences of the control. This suggests to us that members of the control group when considering insurance are more likely to consider historical risks, or at least strongly align these historical beliefs with their

[1] We have also analyzed the willingness to pay on the provincial level. The sample size of Shaanxi and Shandong separately, however, is less the minimum required sample size. Detailed tables can be referenced in Appendix I since the low sample size might show statistically unreliable.

subjective beliefs. The subjective variant differs considerably in WTP from the control across all four WTP attributes and differs from the objective variant in all but the claim starting point.

We are not confident at this point to conclude that our priming on the objective and subjective variants and the differences in WTP are due to affect, because the source of affect is unobservable. Are the differences all about feelings? This is difficult to conclude generally, but even more so in terms of subjective risk perceptions since these may be dominant or subservient to objective risks as illustrated in Figure 1. Furthermore, although the affect heuristic is believed to operate independent of the EUH, the notion of feelings as a concept is ubiquitous and broad (Loewenstein et al. 2001) and it is possible that both operate together either directly or indirectly. A dual process model comes to mind (Wason and Evans 1974; Slovic et al. 2004). A dual process can be comprised of heuristic processes and analytical processes. The initial response is based on the heuristic (e.g. the affect heuristic) whereas the more introspective analytical processes are used to rationalize the choice, whether the choice is erroneous or not. There is nothing in a dual process theory that excludes the EUH as part of the analytical/rationalization process, but the opposite is not generally true; that is the EUH makes no allowances for heuristics.

We explore these issues in the next section. We interact the variables of our CE model with two forms of utility, the first being direct expected utility based on a Taylor Series Expansion, and the second being the certainty equivalent of log utility. A third model creates a scoring rule based on the spread between the cumulative distributions of the subjective and objective probability distributions. We are able to make a determination as to whether unobserved rationalizations based on utility and probabilities had any impact on the WTP measures. We find that this is generally not the case inasmuch as the WTP measures estimates were not materially different than the initial estimates as presented above.

CHAPTER 5

UTILITY CONSIDERATION

5.1 Affect and Risk in Insurance Choices

Choice experiments, according to Harrison and Correal (2012), have three underlying assumptions: risk attitudes, time preference, and subjective beliefs. As a result, one might argue that the choice experiment can be biased since every individual has a different risk premium. In other words, there may be a latent behavioral bias that could influence the decision made by an individual (Andersen et al. 2014; Harrison et al. 2014; Girolamo et al. 2014). Do latent beliefs exist in our experiment, and if so, do they interact in a way that might be consistent with a heuristic/analytical dual process? To test this, we interact moments and probabilities from the PERT distributions illustrated in Figure 1 with the CE attributes.

Our first robustness check is based on a mean-variance-skewness Taylor series expansion of a generic utility function. Recall that the CE by design is a hedonic, multi-attribute utility of undefined form. The expansion around this utility function is given by

$$T\left[U\left(Y\right)\right]=sU\left(\mu_Y\right)+U^{'}\left(\mu_Y\right)\left(Y-\mu_Y\right)+\frac{1}{2}U^{''}\left(\mu_Y\right)\left(Y-\mu_Y\right)^2+\frac{1}{6}U^{'''}\left(\mu_Y\right)\left(Y-\mu_Y\right)^3 \tag{1}$$

Which can be restated in moment form as

$$E\left[U\left(Y\right)\right]=EU\left(\mu_Y\right)+\frac{1}{2}U^{''}\left(\mu_Y\right)E\left(Y-\mu_Y\right)^2+\frac{1}{6}U^{'''}\left(\mu_Y\right)E\left(Y-\mu_Y\right)^3 \tag{2}$$

$$E\left[U\left(Y\right)\right]=EU\left(\mu_Y\right)+\frac{1}{2}U^{''}\left(\mu_Y\right)\sigma^2+\frac{1}{6}U^{'''}\left(\mu_Y\right)\sigma^3 . \tag{3}$$

For convenience, we assume that

$$EU\left(\mu_Y\right)=U\left(E\left[\mu_Y\right]\right)\approx a\mu_Y . \tag{4}$$

In doing so expected utility can be expressed in a linear form convenient for regression analysis.

(5) $E\left[U\left(Y\right)\right]=a\mu_Y+b\sigma^2+c\sigma^3$.

5.2 Certainty Equivalent

Our second robustness test assumes direct expected utility maximization. We assume a LOG utility function

(6) $U\left(Y\right)=LOG\left(Y\right)$.

Using Monte Carlo simulation for each farmer we determine the expected utility across all objective and subjective yield outcomes as measure by the PERT distribution. From these expected utilities we calculate the certainty equivalent yields for each of the subjective and objective distributions:

(7) $CE=Y^*=10^{E\left[LOG(Y)\right]}$.

5.3 Subjective-Objective Scoring Rule

The third measure draws on the concept of stochastic dominance to create a scoring rule that computes the negative or positive spread between subjective and objective yields for each pentile. By comparing the subjective and objective cumulative distributions directly we can determine whether in decision making subjective probabilities dominated objective probabilities, vice versa or not at all. The bounded PERT distributions are defined by $g_S\left(Y;s_L,s_U\right),g_O\left(Y;O_L,O_U\right)$, with cumulative densities $G_S\left(Y\right)=\int_{s_L}^{s_U}g_S\left(Y\right)dY$ and $G_O\left(Y\right)=\int_{O_L}^{O_U}g_O\left(Y\right)dY$.

The stochastic dominance argument is determined by

(8) $$\int_{MIN(S_L,O_L)}^{MAX(S_U,O_U)}\left[G_S\left(Y\right)-G_O\left(Y\right)\right]dY\begin{cases}>0 & if\ \ S\prec O\\ =0 & if\ \ g_S\left(Y\right)=g_O\left(Y\right),\ \forall Y\\ <0 & if\ \ S\succ O\end{cases}.$$

Essentially this relationship sums the difference in increasing cumulative probabilities. If the numerical spread is positive, then that suggests that the objective distribution dominates the subjective distribution. This would arise when the farmer is more pessimistic about future yields than historical yields. If the distributions are identical- that is the objective and subjective PERT distributions are identical in range and mode- the sum of differences will equal zero. Finally, if the sum of differences is negative then that implies that subjective probabilities dominate objective probabilities.

To operationalize this, we use Monte Carlo simulation to obtain the objective and subjective distributions for each farmer. We then define the inverse distribution for a stated (cumulative) probability by $Y_p = G^{-1}(p)$. Our computation measures the difference in crop yields at each probability from 5% to 100% in 5% increments.

$$\int_{MIN(S_L,O_L)}^{MAX(S_U,O_U)} \left[G_S(Y) - G_O(Y)\right] dY \rightarrow \sum_{p=.05,.10...}^{1.00} \left[G_S^{-1}(p) - G_O^{-1}(p)\right] \begin{cases} > 0 & if \quad S \succ O \\ = 0 & if \quad S = O \\ < 0 & if \quad S \prec O \end{cases}$$

5.4 Mean Difference Test

We have already presented some of these results in Figures 1 and 2 which show how individual perceptions can differ and that there is a strong correspondence between subjective and objective mean yields, but weak relationships between subjective/objective standard deviations and skewness. Results in Table 8 show that the mean values of our risk variables are not statistically equivalent. An immediate observation is with the subjective variant group in column 2. In virtually all measures of objective and subjective risk these respondents are significantly higher or lower than the other variants and the aggregate total. Recall that the collection of min, likely, max yield responses was after the CE was complete, so there is no reason giving the

randomization of our sample that these values should be different, which suggests to us that the subjective variant respondents had actually anchored on the variant query. This includes notable differences in the objective and subjective means, objective standard deviations, and objective and subjective certainty equivalents. The ratios of the certainty equivalents, however, were about the same as the objective and control variants. Also, of note is the difference in our stochastic dominance measure. This is measured by the vertical spread between cumulative subjective and objective probabilities, with dominance being assigned to the lower value. For the objective and subjective variants, the results suggest that, on balance, farmers' objective distributions dominate their subjective distributions, but the degree of dominance is lower for the subjective variant. In comparison the control is slightly negative, but close enough to zero to conclude that there is little difference between objective and subjective risks. This is perhaps the strongest evidence that our priming was effective.

Table 8 Mean Difference Test

	Objective	Subjective	Control	Total	Multivariate tests of means
Objective Mean	785.63	835.80	767.16	796.66	Hotelling T2 = 2062.44; Hotelling F (3,1860) = 686.74; Prob > F = 0.0000
Subjective Mean	796.86	843.18	766.57	802.26	Hotelling T2 = 2455.05; Hotelling F (3,1860) = 817.47; Prob > F = 0.0000
Objective Std	66.87	81.19	74.81	74.79	Hotelling T2 = 335.14; Hotelling F (3,1860) = 111.59; Prob > F = 0.0000
Subjective Std	57.50	63.06	63.08	61.47	Hotelling T2 = 218.20; Hotelling F (3,1860) =72.65; Prob > F = 0.0000
Objective Skewness	-0.18	-0.14	-0.10	-0.14	Hotelling T2 = 255.64; Hotelling F (3,1860) = 85.12; Prob > F = 0.0000
Subjective Skewness	-0.11	-0.12	-0.02	-0.08	Hotelling T2 = 194.83; Hotelling F (3,1860) = 64.87; Prob > F = 0.0000
Objective Certainty Equivalent	781.51	830.71	762.64	792.05	Hotelling T2 = 2064.91; Hotelling F (3,1860) = 687.56; Prob > F = 0.0000
Subjective Certainty Equivalent	794.25	840.07	762.87	799.08	Hotelling T2 = 2449.52; Hotelling F (3,1860) = 815.63; Prob > F = 0.0000
Certainty Equivalent Ratio	1.03	1.02	1.01	1.02	Hotelling T2 = 109.01; Hotelling F (3,1860) = 36.30; Prob > F = 0.0000
Stochastic Dominance	251.02	176.05	-1.54	133.41	Hotelling T2 = 103.87; Hotelling F (3,1860) = 34.58; Prob > F = 0.0000
Observation	1,863	2,295	2,349	6,507	

A final observation is warranted on the stochastic dominance scoring function. Figure 3 fits the distribution of the scoring functions rescaled to objective yields. The best-fit distribution based on the Akaike criterion is the double exponential Laplace distribution. Negative values indicate the distribution of respondents where the subjective distribution dominates the objective distribution across mean, variance and skewness. The distribution is centered on zero with about 48% of respondents' beings subjective dominant and 52% being objective dominant. The conditional distributions of each indicates a negative exponential decay with only a small percentage of respondents deviating in a meaningful way from neutrality. By neutrality we mean that for a large proportion of respondents the objective and subjective probability distributions (as illustrated in Figure 1) show considerable overlap. The unscaled means in Table 8, however, reject the null hypothesis that these scores are equal across the three variants and the aggregated sample. Again, because of randomization we find this to be a curious result that appears to be consistent

with the anchoring and adjustment heuristic (Kahneman and Tversky 1973; Lichtenstein et al. 1978; and Morgan and Henrion 1990) since the variant was the only source of exogenous variation attached to the experiment. It is possible (but we cannot prove) that the affect brought about by the subjective prime in the CE model was transferred to the subjective and objective probability measures gathered in the follow-on survey. We cannot exclude, a priori, that anchoring is not a source of bias in the forgoing WTP estimates, but posteriori this does not seem to be the case.

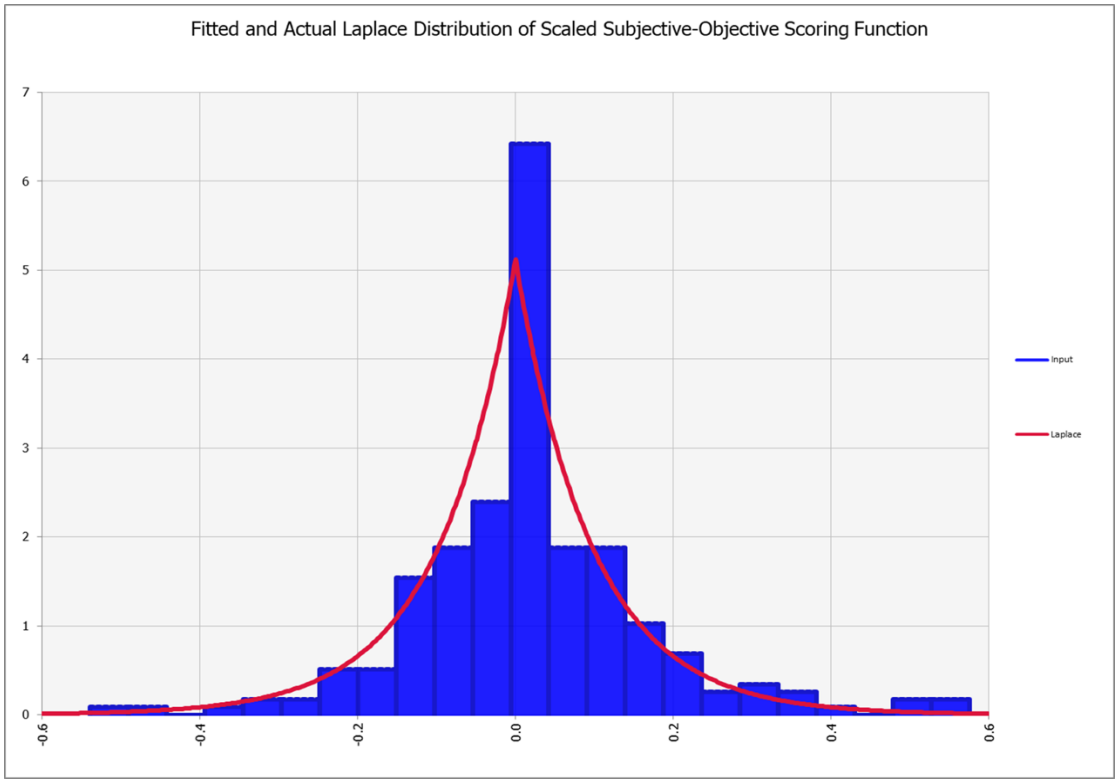

Figure 3. Frequency Distribution of Subjective-Objective Scoring Function

5.5 Willingness to Pay[2]

The results in Table 8 are mixed. The WTP estimates of the Certainty Equivalent and Stochastic Dominance models are highly parsimonious with the original model. The higher standard errors in these models suggest that by introducing the interaction terms adds no new information. In other words, when responding to the initial primed variants, the respondents were consistent in drawing in these two utility measures. This observation is consistent with the dual process model. The primal cue creates affect, but this affect does not stand independently of the utility-centric analytical parameters related to objective and subjective probability distributions. Our results for these two models support this interpretation even when how, and what, respondents consider in their responses is unobservable to us. The same is not true of the EU model. This model does not appear to be parsimonious since the WTP values are inconsistent between this and the baseline model. This is not to say that we can reject the dual process model, since loss of significance in the primal variables suggests at least some presence of multicollinearity. The problem we believe is one of overfitting. With our block design presenting 9-cards with 3 choices per card we have 27 observations per farmer. Yet to capture the EU measures up to the 3rd moment (skewness), there are 5 direct variables and 15*2 (subjective and objective) interaction terms for a total of 35. An overfitted model is unbiased but highly variable and thus less reliable. As a result, while we see some evidence of dual process in the original primal decision, the wildly different WTP measures in the EU model diminishes the evidentiary value provided by this model. This is

[2] Regression results of robust test are provided in the Appendix since most variables are highly statistical insignificant. Regression results of PERT Distribution (Appendix II) show only 17 of 35 variables are statistically significant; and regression results of Certainty equivalent have only 6 of 15 variables are statically significant (Appendix III). The Subjective-Objective scoring model, on the other hand, shows low alteration on our basic results (Appendix IV). Whether the farmer is overconfident or under confident, results have shown that there is no meaningful difference with Table 5, 6, and 7. This gives us the idea that the confidence perception has not played an essential role in our choice experiment, so our experiment stays effective.

a model-specific conclusion. We have high confidence in the certainty equivalent and scoring models to support the conclusion that a dual process is at play, but with differing mechanisms. The high degree of multicollinearity in the certainty equivalent model suggests that the dual processes are highly collinear, or endogenously related. This observation suggests that when primed, these farmers (subliminally) took into consideration the impact of insurance on their choices. The scoring model, however, appears to have had a different effect. There is no evidence of strong multicollinearity in the conditional Logit regression results (Appendix IV) with only two of twenty significant interaction coefficients being significantly different from zero (indemnity-standard deviation for objective variant and loan option-standard deviation for subjective variant). While we cannot exclude the possibility that the analytical form of a scoring function has some influence on the WTP measure the evidence suggest that dual process model applied to the scoring rule is largely independent of the WTP measure reported in Table 9. Nonetheless, the WTP measures across the certainty equivalent and scoring rule models are remarkably consistent with the primary results reported in Table 7 and indicate that our WTP estimates are robust across alternative model specifications.

Table 9 Willingness to Pay

	PERT Distribution				Certainty Equivalent				Stochastic Dominance			
	Objective	Subjective	Control	Total	Objective	Subjective	Control	Total	Objective	Subjective	Control	Total
claim starting point	121.64	-15.45	-74.52	-40.85	59.93	55.38	32.52	46.71	61.16	56.03	30.83	47.75
crop indemnity	-0.47	-0.11	-0.05	-0.16	-0.05	-0.12	-0.07	-0.08	-0.06	-0.13	-0.07	-0.08
types of insurance	-9.82	46.47	13.37	21.11	-12.80	-23.79	-12.73	-16.04	-12.85	-25.63	-13.61	-16.32
loan option	-4.53	-23.67	-8.52	-13.97	-0.76	-11.52	0.36	-2.78	-0.55	-12.12	0.22	-3.20

CHAPTER 7

CONCLUSION

6.1 Conclusion

We have shown farmers' willingness to pay on crop insurance given on the objective or subjective beliefs is in line with the heuristic affect (Loewenstein et al. 2001) and the dual-process theory (Wason and Evans 1974; Slovic et al. 2004). Our experiment validates that priming farmers to anchor on future versus historical risks suggests to us that members of the control group when considering insurance are more likely to consider historical risks. The results highlight that farmers with objective beliefs are more sensitive in the claim starting point and crop premium, and less sensitive in indemnity, insurance types, and credit concern. The subjective variant, similarly, differs considerably in WTP from the control across all four WTP attributes and differs from the objective variant.

More interestingly, we assessed whether the belief distribution has created latent cognitive bias while choosing crop insurance. Farmers could make clear to distinguish between subjective beliefs and subjective probabilities, but latent subjective belief can be elicited through the specification of a utility function (Andersen et al. 2014, Harrison et al. 2014). Combined with utility considerations, the results indicate that the primal cue creates affect, but affect does not stand independently of the utility-centric analytical parameters related to objective and subjective probability distributions. Our choice experiment results effectively illustrate that the objective and subjective beliefs can impacts farmers' willingness to pay for agricultural insurance even with a latent subjective belief based on their utility perception.

Finally, our results suggest a possible role of the objective and subjective beliefs in the crop insurance purchase decision in China. In the insurance context, the contract can be

perceived as being high in benefits when a payoff occurs but low in risk since the most that can be lost is the premium. On the other hand, if the probability of loss is perceived as being low, the loss of premium is viewed as a high risk. In this case, if farmers exhibit systematic biases in how they judge insurance contracts, insurance markets may fail to operate efficiently. From the marketing point of view, insurers should take into consideration how farmers 'feel' about insurance. While farmers will likely consider future risks in terms of their decision, the actuarial structure of insurance will be based largely on past risks. If subjective beliefs differ considerably from these objective actuarial measures, there may be resistance to purchasing insurance. But this is ot a general result since for more than 50% of our cases, farmers subjective beliefs when measured in terms of probabilities, were less confident than their objective beliefs. Another consideration would be that since the expected utility theory is not consistent with the risk aversion, farmers might consider agricultural insurance as an investment tool rather than income protection (Babcock 2015; Dalhaus et al. 2020). Future studies might validate how the prospect theory affects the willingness to pay on the agricultural insurance of farmers.

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APPENDIX

Appendix 1 By Province Willingness to Pay

Table 10 Shaanxi Willingness to Pay

	Objective		**Subjective**		**Control**	
	Conditional Logit	**Mixed Logit**	**Conditional Logit**	**Mixed Logit**	**Conditional Logit**	**Mixed Logit**
claim starting point	-163.47	-137.71	-79.30	-0.01	-15.88	-0.05
crop indemnity	0.09	0.08	0.05	0.04	0.02	0.01
types of insurance	20.61	16.54	19.82	16.38	15.48	13.74
loan option	3.17	6.20	14.71	12.36	0.70	3.33

Table 11 Shandong Willingness to Pay

	Objective		**Subjective**		**Control**	
	Conditional Logit	**Mixed Logit**	**Conditional Logit**	**Mixed Logit**	**Conditional Logit**	**Mixed Logit**
claim starting point	-32.26	-137.71	-34.68	-40.41	-46.21	-52.64
crop indemnity	0.05	0.04	0.21	0.24	0.12	0.10
types of insurance	10.52	7.20	31.76	43.32	11.85	9.36
loan option	0.06	-0.51	9.30	9.39	-1.38	1.17

Appendix 2 Logit Results with PERT Distribution

Table 12 Conditional Logit Result on PERT Distribution

Conditional Logit	Objective	Subjective	Control	Total
claim starting point	-3.543	-1.231	-1.258	-1.036
crop premium	-0.00181	-0.00484	-0.0453**	-0.0255*
crop indemnity	-0.00122	-0.00460**	-0.00376**	-0.00285**
types of insurance	0.0631	0.337	1.055***	0.609***
loan option	-0.536	1.327***	0.0805	0.185
Claim _ submean	-1.161	-0.120	-0.926	-0.397
Premium _ submean	-0.00760	-0.00751	-0.000247	-0.00227
Indemnity _ submean	-0.000839	0.000700*	0.000964**	0.000392*
Types _ submean	0.0543	-0.000223	-0.0879	-0.0468
Loan option _ submean	0.102	-0.220**	0.0265	-0.0355
Claim _ substd	1.274	0.574	0.384	0.287
Premium _ substd	0.00549	0.00237	-0.00540	-0.000530
Indemnity _ substd	0.00115**	0.000316	-0.000224	0.000280
Types _ substd	0.0195	0.107	0.0643	0.0629
Loan option _ substd	-0.103	0.145*	0.0137	0.0529
Claim _ subskew	-0.0105	-0.0422**	0.0503*	-0.00189
Premium _ subskew	-0.000273	4.04e-05	0.000606**	0.000159
Indemnity _ subskew	9.06e-06	-2.67e-05*	2.32e-05	2.91e-06
Types _ subskew	-0.00231	-0.00822***	-0.00612*	-0.00393**
Loan option _ subskew	0.00235	-5.97e-05	0.000676	0.000916
Claim _ obmean	-0.00375	-0.00733	0.00858	0.00468
Premium _ obmean	-0.000309	0.000214	3.53e-05	-3.44e-05
Indemnity _ obmean	2.19e-05	3.40e-05**	-8.08e-06	8.40e-06
Types _ obmean	0.00313	0.000766	0.00174	0.00201
Loan option _ obmean	0.00735*	-0.00591*	-0.00674**	-0.00442***
Claim _ obstd	-1.551	-0.170	1.930	0.375
Premium _ obstd	0.00189	0.0163	0.0337**	0.0146*
Indemnity _ obstd	0.00178*	0.00157	0.00159	0.00198***
Types _ obstd	0.0317	-0.903***	-0.441**	-0.342***
Loan option _ obstd	0.105	0.300	0.229	0.148
Claim _ obskew	-0.328	1.164	-0.997	-0.0464
Premium _ obskew	-0.0127	-0.0269**	0.0122	-0.00657
Indemnity _ obskew	-0.00148*	-0.000402	-0.00106	-0.00113**
Types _ obskew	0.104	0.233	-0.386**	-0.0989
Loan option _ obskew	-0.146	-0.226	-0.105	-0.112
Observations	1,863	2,295	2,349	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 13 Mixed Logit Result on PERT Distribution

Mixed Logit	**Objective**		**Subjective**		**Control**		**Total**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Claim _ submean	-2.187		-0.283		-1.335		-0.727	
Premium _ submean	-0.0389*		-0.0120		-0.00106		0.00101	
Indemnity _ submean	-0.000770		0.000752		0.00147**		0.000770	

Types _ submean	0.0647		0.0782		-0.147		-0.0224	
Loan option _ submean	0.340		-0.174		0.0167		0.0258	
Claim _ substd	2.032		0.917		0.571		0.486	
Premium _ substd	0.0440**		0.00343		-0.00683		-0.00471	
Indemnity _ substd	0.00149		0.000660		-0.000520		8.04e-05	
Types _ substd	0.0627		0.0647		0.100		0.0738	
Loan option _ substd	-0.226		0.103		0.0234		0.0266	
Claim _ subskew	-0.0146		-0.0456		0.0678**		0.00336	
Premium _ subskew	-0.000965*		7.85e-05		0.000723*		0.000140	
Indemnity _ subskew	-7.74e-06		-4.77e-05*		1.28e-05		-5.45e-06	
Types _ subskew	-0.00372		-0.0140**		-0.00420		-0.00697**	
Loan option _ subskew	0.00537		-0.000366		0.00267		4.74e-06	
claim starting point	0.0521		-0.0400		0.00659		-0.00800	
crop premium	-0.000775		0.000302		7.12e-05		5.62e-05	
crop indemnity	4.58e-05		6.15e-05**		-3.43e-07		2.07e-05	
types of insurance	0.00346		-0.00129		0.00326		0.00379	
loan option	0.0209**		-0.00932**		-0.00830**		-0.00551**	
Claim _ obmean	-4.586		0.860		1.966		-0.0357	
Premium _ obmean	-0.0384		0.0294		0.0356		0.0113	
Indemnity _ obmean	0.00211		0.00242		0.00152		0.00141	
Types _ obmean	0.0762		-1.614***		-0.474		-0.471**	
Loan option _ obmean	0.351		0.277		0.304		0.210	
Claim _ obstd	-0.483		1.954		-0.845		-0.0918	
Premium _ obstd	0.00987		-0.0337		0.0250		-0.00710	
Indemnity _ obstd	-0.000658		-0.000838		-0.00140		-0.000837	
Types _ obstd	0.103		0.458		-0.748**		-0.107	
Loan option _ obstd	-0.279		-0.295		-0.199		-0.0777	
Claim _ obskew	-7.615	-12.78***	-0.895	-6.301***	-1.481	0.281	-0.843	-5.576***
Premium _ obskew	-0.0640	0.143***	-3.62e-05	0.0708***	-0.0563	0.0579***	-0.0470	0.0831***
Indemnity _ obskew	-0.00175	0.00481***	-0.00664	0.00558***	-0.00431	0.00405***	-0.00290	-0.00528***
Types _ obskew	-0.152	1.762***	0.878	-1.088***	1.108*	1.186***	0.706	1.245***
Loan option _ obskew	-2.229**	-1.478***	1.587**	0.296	0.0489	0.636***	0.139	0.865***
Observations	1,863	1,863	2,295	2,295	2,349	2,349	6,507	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 3 Logit Results with Certainty Equivalent

Table 14 Conditional Logit Result on Certainty Equivalent

Conditional Logit	**Objective**	**Subjective**	**Control**	**Total**
claim starting point	-5.150	-2.324	1.784	-1.010
crop premium	-0.0367	-0.0118	-0.0155	-0.0211
crop indemnity	-0.000131	-0.00357*	-0.00311**	-0.00228**
types of insurance	0.119	0.260	0.786***	0.437**
loan option	-0.0993	1.002**	-0.117	0.0693
Claim _ subce	-0.00908	-0.00254	-0.00369	-0.00357
Premium _ subce	-6.96e-05	-4.49e-05	5.26e-05	-1.60e-05
Indemnity _ subce	-1.12e-05**	6.86e-06*	1.21e-05***	3.62e-06
Types _ subce	0.000887	-0.000564	-0.00124	-0.000418
Loan option _ subce	0.000735	-0.00267***	0.000415	-0.000567
Claim _ obce	0.0118	0.00352	-0.000237	0.00262
Premium _ obce	5.21e-05	2.45e-05	-8.60e-05	-5.54e-06
Indemnity _ obce	1.48e-05***	1.85e-06	-4.37e-06	3.09e-06
Types _ obce	-0.000220	0.00109	0.000927	0.000645
Loan option _ obce	-0.000567	0.00184***	-0.000290	0.000619
Observations	1,863	2,295	2,349	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15 Conditional Logit Result on Certainty Equivalent

Mixed Logit	**Objective**		**Subjective**		**Control**		**Total**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
claim_obce	-0.00847		-0.00329		-0.00729		-0.00439	
premium_obce	-0.000415**		-0.000100		5.39e-05		2.34e-05	
indemnity_obce	-2.26e-05**		1.18e-05		1.41e-05**		7.19e-06*	
types_obce	0.00469**		-0.000572		-0.000303		-0.000175	
Loan option_obce	-0.000379		-0.00232**		0.000681		-0.000253	
claim_subce	0.0184		0.00288		0.00135		0.00133	
premium_subce	0.000382**		0.000119		-9.81e-05		-7.30e-05	
indemnity_subce	2.70e-05***		2.53e-06		-4.55e-06		2.72e-06	
types_subce	-0.00341		0.00153		4.50e-05		0.00118	
Loan option_subce	0.000198		0.00134		-0.000365		0.000590	
claim starting point	-13.35*	-11.23***	-2.095	7.197***	2.586	0.165	-0.411	-5.894***
crop premium	-0.0849	0.108***	-0.0596	0.0845***	-0.0249	0.0604***	-0.0226	0.0801***
crop indemnity	0.00164	-0.00492***	-0.00677*	-0.00641***	-0.00393*	0.00416***	-0.00310*	0.00528***
types of insurance	-0.194	1.595***	0.235	1.389***	0.915	1.181***	0.138	-1.290***
loan option	0.201	1.376***	1.222**	0.443**	-0.247	-0.650***	-0.133	0.868***
Observations	1,863	1,863	2,295	2,295	2,349	2,349	6,507	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 4 Logit Results with Subjective-Objective Scoring Function

Table 16 Conditional Logit Result on Stochastic Dominance

Conditional Logit	Objective	Subjective	Control	Total
claim starting point	-3.130***	-1.568**	-1.279**	-1.853***
crop premium	-0.0503***	-0.0279***	-0.0409***	-0.0384***
crop indemnity	0.00273***	0.00360***	0.00277***	0.00304***
types of insurance	0.645***	0.705***	0.557***	0.623***
loan option	0.0312	0.325***	-0.00666	0.120**
Claim _ sd	0.000565	0.000139	1.72e-05	0.000154
Premium _ sd	2.69e-06	1.83e-06	-3.81e-06	1.66e-07
Indemnity _ sd	6.12e-07***	-2.82e-08	-2.97e-07	2.46e-08
Types _ sd	-2.29e-05	2.95e-05	4.95e-05	2.44e-05
Loan option _ sd	-2.83e-05	7.74e-05**	-1.76e-05	2.15e-05
Observations	1,863	2,295	2,349	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 17 Mixed Logit Result on Stochastic Dominance

Mixed Logit	**Objective**		**Subjective**		**Control**		**Total**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
claim_sd	0.000601		0.000378		5.20e-06		0.000119	
premium_sd	5.89e-06		1.69e-07		-3.16e-06		-5.61e-07	
indemnity_sd	3.57e-07		-1.58e-07		-3.83e-07		2.08e-08	
types_sd	8.42e-06		6.35e-05		5.54e-05		5.34e-05	
loanoption_sd	-4.77e-05		5.60e-05		-3.40e-05		9.62e-06	
claim starting point	-4.954***	9.212***	-3.034***	-6.804***	-1.961**	1.510	-2.949***	-5.718***
crop premium	-0.124***	0.146***	-0.0476***	0.0701***	-0.0586***	0.0648***	-0.0630***	0.0841***
crop indemnity	0.00479***	0.00607***	0.00493***	-0.00620***	0.00344***	0.00451***	0.00436***	0.00553***
types of insurance	0.994***	1.737***	1.107***	1.415***	0.624***	1.226***	0.879***	1.368***
loan option	-0.0461	1.539***	0.393***	0.430**	0.0174	0.732***	0.161*	0.856***
Observations	1,863	1,863	2,295	2,295	2,349	2,349	6,507	6,507

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 5 Survey

Survey of Villagers to Assess Crop Insurance

NARRATIVE TO BE READ TO RESPONDENTS: First of all I would like to thank you for taking the time to meet with us. This survey should take approximately 10 minutes and again I thank you for your time. The survey we are conducting is a joint product between xx university and Cornell University in the United States. We are interested in collecting information in relation to credit. Your responses will be completely confidential and under no circumstances will your responses be identifiable. In addition we understand that you may not have all of the precise information available. In these cases all we ask is that you provide us with your best estimates or best judgments. Finally, you have the right to refuse to answer any question we might ask.

Given these objectives are you willing to participate in this survey? Yes No

If NO then "*Ok, that is fine. For our records can you tell us why you do not want to participate?*

NOTE to interviewer: *If answer above is because respondent does not feel they have the information we need then ask why and explain again that we only require a best effort on their part, and that we expect that not all respondents will have precise information. And then ask if they will reconsider.*

NOTE to interviewer: If answer above is related to privacy issues, then remind respondent that their participation will be most helpful to our research and that they will remain anonymous and that their privacy is guaranteed. And then ask if they will reconsider.

IF YES…." *Thank you very much for your consent. Let us begin. We would like to start off by asking some general questions about your farm household*"……. Go to question 1. DO NOT RECORD NAME OF RESPONDENT

Village _____

Date _____

Interviewer _____

Number	Category	Question	Unit	
A1	Farm Characteristics	Gender	0=Female, 1=Male	
A2		Age		
A3		Including yourself how many people live in this house	Number of people	
A4		How many members of your household are primarily involved in agricultural work	Number of people	
A5		How many members of your household earn off-farm wages	Number of people	
A6		Are you the primary decision maker in agricultural affairs	0=No, 1=Yes	
A7		Do any household members work for village leader, village committee, state government, county government, state enterprise, and RCC or banks)	0=No, 1=Yes	
A8		What is your education level	0=Never Went to School, 1=At least elementary school, 2=At least middle school, 3=At least high school, 4=Some University or college, 5=Completed College or University	
A9		How many years have you been farming		
A10		What is the total size of your household farm (Mou, allocated Land Use rights, excluding land rented in)		
A11		How much land do you rent in for agricultural use (total mou rented)	Mu	
A12		In general, how would you describe the current agricultural business in your area compared to last year	1=Getting worse, 2=About the same, 3=Getting better	
A13		Please list the top five crops you have grown in the past 12 months from the most valuable to the least valuable	1	
			2	

			3	
			4	
			5	
A14		Farm income	Yuan	
A15		Off-farm income	Yuan	
A16		Total income	Yuan	
A17		Productive expenditure	Yuan	
A18		Household Consumption expenditures (food, clothes, health, education, etc.)	Yuan	
A19		Other expenditures (e.g. car, house, vacation travel)	Yuan	
A20		Gross Incomes minus Expenditures	Yuan	
B1	Sources of Risk and Risk Perceptions	Accepting greater production risks to increase the chance of higher profits is important to me	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
B2		I am more likely to take risks with new agricultural technologies (mechanical or management practices or input use) before I see good results on other farms	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
B3		I am willing to take risks with new management practices before I see good results in other farms	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
B4		Diversifying my crop (including livestock) mix in order to reduce risk is important to me	5=Strongly Disagree, 4=Moderately Disagree, 3=Agree, 2=Moderately Agree, 1=Strongly Agree	
B5		Having different Fields or farms at different locations (geographic diversification) is important to me	5=Strongly Disagree, 4=Moderately Disagree, 3=Agree, 2=Moderately Agree, 1=Strongly Agree	
B6		I would consider growing more risky crops if I had (or have) greater access to irrigation	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	

B7		I would, or do, sell my agricultural products over a period of time rather than at harvest in order to reduce market price risk (diversified marketing)	5=Strongly Disagree, 4=Moderately Disagree, 3=Agree, 2=Moderately Agree, 1=Strongly Agree	
B8		I have (or would if I could) made some non-farm investments in new business in order to diversify household income.	5=Strongly Disagree, 4=Moderately Disagree, 3=Agree, 2=Moderately Agree, 1=Strongly Agree	
B9		I am willing to ACCEPT more risk in all aspects of life relative to my peers (other farmers that you know)	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
B10		In general, I believe that I TAKE more risks in all aspects of life than my peers.	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C1	Precautionary Savings	What proportion of Household income (define income here as revenues minus productive expenses minus consumption and other non-productive expenditures) are you able to save in a year	1=none, 2=less than 5%, 3=3%-5%, 4=more than 10%	
C2		I save in case my house needs repair	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C3		I save in case my automobile (e.g. car, motorcycle, tractor) breaks down.	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C4		I save in case I cannot repay a loan from earnings.	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C5		I save for unexpected medical emergency	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	

C6		I save in case I lose my job	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C7		I save for unanticipated crop loss.	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
C8		In your opinion, do you think saving is important?	1=Strongly unimportant, 2=Moderately unimportant, 3=important, 4=Moderately important, 5=Strongly important	
D1	Predicted and Historical Yield	If you grow corn or wheat, identify the lowest yield you believe possible, the yield that you believe is most likely to be receive, and the highest possible yield you believe possible (Jin/Mu) where (1jin = 500g) in upcoming crop season	Corn	
			Wheat	
D2		What is the percentage chance that your yields in the upcoming crop year will fall outside the range of the Lowest and Highest values reported above		
D3		What is the percentage chance that your yields in the next crop year will be at least as high as the most likely yield you reported above		
D4		If you grow corn or wheat, what is the lowest, most likely to receive, and highest yield (Jin/Mu) that you recall from your years in farming? If you do not recall exacts, please answer to nearest within 10 Jin/Mu.	Corn	
			Wheat	

E1	Crop Insurance Use and Perceptions	How much do you know about crop insurance	1=I never heard of crop insurance, 2=I know nothing about crop insurance, 3=I know a little about crop insurance, 4=I know crop insurance well	
E2		Is crop insurance currently available to you (if yes skip to E4)	1=Yes, 2=No, 3=Not sure	
E3		If crop insurance was offered in your region next crop season do you think that you would purchase crop insurance (If Yes skip to E10; If No skip to E11)	0=No, 1=Yes	
E4		Have you purchased crop insurance (If No skip to E11)	0=No, 1=Yes	
E5		In what year did you first purchase crop insurance		
E6		Whether the listed crops covered; How much do you pay per Mu; Have you ever received the indemnity	Corn	
			Wheat	
E7		For most crops, crop insurance is subsidized by up to 80% of its fair value. For example, if you pay 3RMB/Mu the true cost would be 15 RMB/Mu. Would you still purchase crop insurance if you had to pay 15 RMB/Mu, an increase of 5 times the current rate	1=Definitely not purchase, 2=Will unlikely purchase, 3=Will likely purchase, 4=Will definitely purchase	
E8		(If definitely not or unlikely in E7) You responded that you are unlikely to purchase crop insurance if the price rose from 3RMB to 15RMB/Mu. Would you change your mind if you received a 50% subsidy so that the price was 7.5 RMB/Mu	1=Definitely not purchase, 2=Will unlikely purchase, 3= Will likely purchase, 4=Will definitely purchase	

E9		If the cost of insurance remains the same as your last purchase, will you continue to purchase insurance for the next crop	1=Definitely not purchase, 2=Will unlikely purchase, 3= Will likely purchase, 4=Will definitely purchase	
E10		Why do you purchase crop insurance? a. The insurance premium is affordable b. Crop yield in previous year was low c. The probability of future climatic risk occurrence is high d. Change in the local climate has caused damage to our crops e. Government subsidizes the insurance premium f. My relatives or friends purchase crop insurance g. The richest person (or leader) in my village purchases crop insurance h. There are many propagandas in my village that encourages farmer to purchase crop insurance	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	

E11		Why not you or would not purchase crop insurance. a. I will not purchase crop insurance because I do not have enough money to pay for it b. I will not buy crop insurance because I do not believe that it is necessary c. I will not buy crop insurance because I don't trust the insurer to compensate me if the insurance is triggered d. I will not buy crop insurance because I do not understand how crop insurance works e. I will not buy crop insurance because it is offered by a private insurance company and I would prefer to buy crop insurance from a government agency f. I will not buy crop insurance because the payout if the insurance is triggered is too low	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E12		If the frequency of disaster gets higher, would you be more willing to purchase a crop insurance	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E13		If the premium per Mu gets lower, would you be more willing to purchase a crop insurance	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E14		If the indemnity per Mu gets higher, would you be more willing to purchase a crop insurance	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E15		If a crop insurance is provided by a state-owned firm instead of a private one, would you be more willing to purchase it	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	

E16		If a crop insurance is acceptable as loan collateral, would you be more willing to purchase a crop insurance	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E17		I believe that purchasing crop insurance will reduce my production risks which will better enable my ability to repay money I borrowed from banks, friends and/or relatives	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E18		If I purchase crop insurance, it will increase my chances of obtaining a loan from an RCC or another formal bank	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E19		I believe that by purchasing crop insurance I can increase the amount of money I can borrow from RCC or other formal banks	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E20		I believe that crop insurance would become more important to me if I were to increase my farming operation by renting land (production rights) from a Land Transfer Center or from private individuals	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
E21		Have you ever purchased other types of insurance (for example, life insurance, fire insurance, automobile insurance)	0=No, 1=Yes	
F1	Answered by interviewer only	Do you think the respondent was engaged in this survey and answered truthfully all questions	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	
F2		Do you think the quality of answers provided in this survey is adequate to include in any written reports	1=Strongly Disagree, 2=Moderately Disagree, 3=Agree, 4=Moderately Agree, 5=Strongly Agree	