THREE ESSAYS ON FARMERS' CROP INSURANCE CHOICES: EXPERIMENTAL EVIDENCE FROM CHINA

by

RAN HUO

(Under the Direction of Octavio Ramirez and Greg Colson)

ABSTRACT

This dissertation includes three essays investigating smallholder farmers' demand for crop insurance in China using data from a series of economic surveys and experiments with 477 vegetable farmers in China. The first essay focuses on farmers' preferences for crop insurance under alterative frames and coverage level. The empirical findings, when viewed through the lens of expected utility theory, reveal three anomalies. First, we find that farmers tend to place less value on a risk-reducing contract framed in the context of crop insurance compared to an otherwise equivalent contract not framed as insurance. Second, farmers place a relatively higher value on low coverage contracts compared to high coverage contracts. Third, farmers who are more risk averse or loss averse are found to be less willing to purchase crop insurance with a high coverage level.

Building upon these findings, the second essay reconciles these anomalous findings within a prospect theory framework under narrow framing. Recognizing that farmers in rural areas of developing countries may have less experience with crop insurance and less trust in the institutions managing crop insurance suggests that farmers may tend to view crop insurance as an innovative technology rather than a risk-transferring tool. Empirical tests indicate support for this conjecture. We find that farmers' decisions in the surveys and experiments correspond with theoretical predictions under prospect theory for an agent who evaluates a crop insurance purchase deception independently from their crop revenue.

Focusing on the challenge for farmers to evaluate crop insurance policies and estimate the actuarially fair premium underlying a policy, the third essay develops a probabilistic model incorporating biased estimates of the actuarially fair premium in order to explain economically suboptimal take-up of crop insurance by smallholder farmers. Evidence from the probabilistic model employing data from the economic surveys and experiments partially explains the anomalous decisions found in the first essay. Critically, we find that farmer's risk aversion, average propensity to consume, and other key sociodemographic variables have explanatory power for farmers' willingness to pay for a crop insurance contract and farmers' estimate of the actuarially fair premium for a crop insurance contract.

INDEX WORDS: Small Farms, Crop Insurance, China, Prospect Theory, Risk Aversion, Loss Aversion, Reference Point

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

For farmers in developing markets, lack of disaster protection mechanisms has been identified as a significant barrier to long-term sustainable and economically viable agricultural production. (Morduch, 1995; Boucher et al., 2008; Gaurav, 2014). One such mechanism, government supported crop insurance programs, has emerged in many developed counties such as the United States as the primary policy approach to support farmers and mitigate risks to farm revenue due to natural risks. Since the late 1990s, crop insurance programs for smallholder farmers have been piloted in array of developing countries in Africa, Asia, and Latin America (Hazell et al., 1992; Boucher and Mullally, 2010; Cole et al., 2013; Giné and Yang, 2009). However, many of the pilot programs experienced low uptake by farmers even when insurance policy premiums were heavily subsidized by the government and were eventually discontinued (Miranda and Farrin, 2012). A critical question, which is the focus of this dissertation, is understanding why farmers have unexpectedly low spontaneous desire to purchase crop insurance, which plays a critical role in building farm safety nets (Hazell et al, 1992; Giné et al. 2009), and potential avenues to improve crop insurance program designs to increase farmer uptake.

Previous studies discussing low demand by farmers for crop insurance in developing countries have primarily focused on index insurance, which conceptually is an effective market-based risk management instrument to protect smallholders against weather-related crop losses. A variety of explanations for low index insurance take-up include farmers’ lack of trust, financial literacy or knowledge in disaster probability and exterior deficiencies, such as poor quality of contract design, incomplete information, limited credit accessibility. Giné et al. (2008) used household survey data to explore farmers' demand for rainfall index insurance and disclosed a set of factors that are closely related to farmers' insurance take-up decisions, including credit constraints, basis risk, risk aversion, trust and so forth. Their results reflect smallholder farmers' uncertainty about the product, given their limited experience with it. Cole et al. (2012) conducted a series of randomized field experiments in rural India to test the impact of price and non-price factors on farmers' rainfall insurance take-up including group insurance, historical payouts and contract design. Cai and Song (2013) designed field experiment to test the effect of disaster experience and knowledge and concentrate on index insurance take-up in China. Karlan et al. (2013) examined the impact of networks and experience of receiving payouts in the previous year on insurance take-up. Cole (2013) examined a seven-year panel data of rainfall insurance purchase decisions made by rural farming households in India. Their findings suggested the experience in insurance payouts especially multiple time payouts increase famers' take-up. Elabed and Carter (2015) designed framed field experiments with cotton farmers in Southern Mali to test the impact of basis risk on the demand for index insurance. They posited that farmers are compound risk averse and they used smooth model rather than Expected Utility Model to assess farmers' perceptions of basis risk. Petraud et al. (2015) elicited risk preference parameters from a series games with smallholder cotton farmers in southern Peru and tested the effectiveness of Cumulative Prospect Theory (CPT) and Expected Utility Theory (EUT) in predicting farmers' insurance choices.

In this dissertation, we build upon these findings and focus on three critical questions. First, is low demand for crop insurance partially explained simply by intrinsic resistance by farmers to insurance per se, potentially due to lack of trust in crop insurance institutions? Second, what is the relationship between the coverage levels offered for crop insurance policies and farmer demand for insurance? Third, given the inherent difficulties for individual farmers to determine actuarially fair premiums, does bias in farmer estimates partially explain low demand for crop insurance? In this dissertation, these questions are explored against the backdrop of two competing economic theories of decision making under risk and uncertainty, expected utility theory and prospect theory, using data from a series of economic surveys and experiments with 477 vegetable farmers in China. Data includes farmer demand for crop insurance under different frames, coverage levels, and subsidy rates as well as measures of farmer risk aversion, loss aversion, and probability weighting. The remainder of the dissertation is organized in three essays as follows.

The first essay focuses on farmers' preferences for crop insurance under alterative frames and coverage levels. The empirical findings, when viewed through the lens of expected utility theory, reveal three anomalies. First, we find that farmers tend to place less value on a risk-reducing contract framed in the context of crop insurance compared to an otherwise equivalent contract not framed as insurance. Second, farmers place a relatively higher value on a crop insurance policy with a low coverage level compared to a policy with a high coverage level. Third, farmers who are more risk averse or loss averse are found to be less willing to purchase crop insurance with a high coverage level.

Building upon these findings, the second essay reconciles these anomalous findings within a prospect theory framework under narrow framing. Recognizing that smallholder farmers in rural areas of developing countries may have less experience with crop insurance and less trust in the institutions managing crop insurance suggests that farmers may tend to view crop insurance as an innovative technology rather than a risk-transferring tool. Empirical tests indicate support for this conjecture; our data suggests that farmers are narrow framers, meaning they tend to view crop insurance as an investment independent from other risks. Under such finding, prospect theory does a better job at explaining smallholder farmers' crop insurance choices than conventional theory.

Focusing on the challenge for farmers to evaluate crop insurance policies and estimate the actuarially fair premium underlying a policy, the third essay develops a probabilistic model incorporating biased estimates of the actuarially fair premium in order to explain economically suboptimal take-up of crop insurance by smallholder farmers. Evidence from the probabilistic model employing data from the economic surveys and experiments partially explains the anomalous decisions found in the first essay. Critically, we find that farmer risk aversion, average propensity to consume, and other key sociodemographic variables have explanatory power for farmers' willingness to pay for a crop insurance contract and farmers' estimate of the actuarially fair premium for a crop insurance contract.

BIBLIOGRAPHY

Boucher, S. and Mullally, C., 2010. Evaluating the Impact of Index Insurance on Cotton Farmers In Peru. *Technical Notes IDB TN*, 198.

Boucher, S.R., Carter, M.R. and Guirkinger, C., 2008. Risk Rationing and Wealth Effects in Credit Markets: Theory and Implications for Agricultural Development. *American Journal of Agricultural Economics*, 90(2), pp.409-423.

Cai, J. and Song, C., 2017. Do Disaster Experience and Knowledge Affect Insurance Take-Up Decisions?. *Journal of Development Economics,* 124, pp.83-94.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J., 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics,* 5(1), pp.104-35.

Cole, S., Sampson, T. and Zia, B., 2011. Prices or knowledge? What Drives Demand for Financial Services in Emerging Markets? *The Journal of Finance,* 66(6), pp.1933-1967.

Elabed, G. and Carter, M.R., 2015. Compound-Risk Aversion, Ambiguity and the Willingness to Pay for Microinsurance. *Journal of Economic Behavior & Organization,* 118, pp.150-166.

Galarza, F., 2009. Choices under Risk in Rural Peru. *University of Wisconsin-Madisson.*

Gaurav, S., Cole, S. and Tobacman, J., 2011. Marketing Complex Financial Products in Emerging Markets: Evidence from Rainfall Insurance In India. *Journal of Marketing Research,* 48(SPL), pp.S150-S162.

Giné, X. and Yang, D., 2009. Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi. *Journal of Development Economics*, 89(1), pp.1-11.

Giné, X., Townsend, R. and Vickery, J., 2007. Patterns of Rainfall Insurance Participation in Rural India. *The World Bank.*

Harrison, G.W., Humphrey, S.J. and Verschoor, A., 2009. Choice under Uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal*, 120(543), pp.80-104.

Hazell, P., Anderson, J., Balzer, N., Hastrup Clemmensen, A., Hess, U. and Rispoli, F., 2010. The Potential for Scale and Sustainability in Weather Index Insurance for Agriculture and Rural Livelihoods. *World Food Programme (WFP).*

Hill, R.V., Hoddinott, J. and Kumar, N., 2013. Adoption of Weather ‐ Index Insurance: Learning from Willingness to Pay among a Panel of Households in Rural Ethiopia. *Agricultural Economics,* 44(4-5), pp.385-398.

Hill, R.V., Robles, M. and Ceballos, F., 2016. Demand for a Simple Weather Insurance Product in India: Theory and Evidence. *American Journal of Agricultural Economics,* 98(4), pp.1250-1270. Karlan, D., Kutsoati, E., McMillan, M. and Udry, C., 2011. Crop Price Indemnified Loans for Farmers: A Pilot Experiment in Rural Ghana. *Journal of Risk and Insurance,* 78(1), pp.37-55.

Lybbert, T.J., Galarza, F.B., McPeak, J., Barrett, C.B., Boucher, S.R., Carter, M.R., Chantarat, S., Fadlaoui, A. and Mude, A., 2010. Dynamic Field Experiments in Development Economics: Risk Valuation in Morocco, Kenya, and Peru. *Agricultural and Resource Economics Review*, 39(2), pp.176-192.

Miranda, M.J. and Farrin, K., 2012. Index Insurance for Developing Countries. *Applied Economic Perspectives and Policy,* 34(3), pp.391-427.

Morduch, J., 1995. Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives,* 9(3), pp.103-114.

Petraud, J., Boucher, S. and Carter, M., 2015. *Competing Theories of Risk Preferences and the Demand for Crop Insurance: Experimental Evidence from Peru* (No. 1008-2016-80041).

CHAPTER 2

INSURANCE DEMAND OVER VARYING COVERAGE LEVELS[1]

[1] Ran Huo and Greg Colson. To be submitted to American Journal of Agricultural Economics.

Abstract

Low demand for crop insurance, even when subsidized at highly actuarially favorable rates, is a challenge for policymakers in developing countries trying to create insurance-based farm safety nets. Contributing to the larger literature exploring drivers of low uptake of crop insurance, we measure not just take-up rate for insurance, but demand for insurance over varying coverage levels. Further, to assess farmers' intrinsic resistance to crop insurance potentially due to negative opinions or confidence in the risk management approach, we examine farmers' decisions framed both in an insurance context and in a neutral-frame without mentioning the name of insurance. Evidence from a series of surveys and experiments with 477 vegetable farmers in China reveals several anomalies in farmers' demand for crop insurance and deviations from predictions by conventional theories. The empirical findings, when viewed through the lens of expected utility theory, reveal three anomalies. First, we find that farmers tend to place less value on a risk-reducing contract framed in the context of crop insurance compared to an otherwise equivalent contract not framed as insurance. Second, farmers place a relatively higher value on low coverage contracts compared to high coverage contracts. Third, farmers who are more risk averse or loss averse are found to be less willing to purchase crop insurance with a high coverage level. Our data also suggests high government subsidy has limited ability to mitigate the distortions in crop insurance choices.

2.1 INTRODUCTION

Lack of disaster risk protection mechanisms in developing markets has proven to be a significant hurdle to developing sustainable farm safety nets (Morduch, 1995; Boucher et al., 2008; Gaurav, 2014). Why farmers have low spontaneous desire to purchase crop insurance and potential institutional, policy, and outreach efforts to overcome barriers to crop insurance adoption, have been recent active areas of agricultural and development economics research. Most relevant research studies concentrate on the lack of demand for index insurance, given that index insurance has been seen as an emerging effective market-based risk management instrument to protect smallholders against weather-related crop losses. A variety of explanations end empirical evidence for the low demand for have been suggested including lack of trust, financial literacy or knowledge in disaster probability (Gaurav et al., 2011; Cole et al., 2013; Cai et al., 2015) and exterior deficiencies, such as poor quality of contract design, incomplete information, limited credit accessibility (Giné et al., 2013; Gelade 2011; Giné et al., 2008). The presence of these barriers potentially forms a negative opinion of crop insurance among farmers in emerging markets and potentially leads to crop insurance decisions that run counter to conventional economic theory of individual decision making under risk and uncertainty. If a prevalent negative opinion rises, farmers are likely to evaluate insurance less than an equivalent contract not framed as insurance. Often, the negative opinion might be resulted from the insurance supply side, such as the poor contract design or incompletely contract implementation. On the other hand, misunderstanding of crop insurance and resulting overly high expectation may also lead to farmers' negative opinion.

How do we assess the effect of farmers' intrinsic resistance to crop insurance potentially due to negative opinions or confidence in risk management approach? How does the intrinsic resistance affect farmers' choice on insurance coverage level? Would providing high premium subsidy mitigate the outcomes resulted from the resistance? In this study we provide new empirical evidence from a series of surveys and economic experiments with 477 vegetable farmers in China and explore their demand for crop insurance under alternative frames, coverage levels, and subsidy rates. In the survey, we used a unique framed experiment to measure farmers' intrinsic resistance to crop insurance. We also conducted experiments to elicit farmers' risk preference and coverage choices with and without subsidy rates.

The data disclosed strong anomalies in farmers' choices, which can be described in three aspects. First, farmers tend to be willing to pay lower price for an insurance contract than an equivalent non-insurance framed contract. Second, on an aggregated level, farmers are more likely to buy insurance priced at the actuarially fair premium (AFP) for low coverage insurance levels than for high coverage levels, which is inconsistent with the Expected Utility Theory (EUT). By EUT, a risk averse individual will pursue full coverage when the premium of the insurance policy is actuarially fair (Mossin, 1968); thus, she will prefer full coverage over partial coverage if given AFP. Second, at the individual level, risk and loss averse farmers are more likely to buy higher coverage levels than risk tolerant and loss tolerant farmers. The negative effects of risk aversion have been discussed in previous studies (Giné et al., 2008; Cole et al., 2013; Hill et al., 2013a). To the best of our knowledge, there is no published study exploring the relationship between insurance frame, risk preference and farmers' coverage choices of crop insurance in an emerging market. A similar finding regarding the inverse relationship between insurance demand and loss aversion can be seen in the working study by Shin et al. (2018). Using a data from Ghana, they show that loss averse farmers are less likely to purchase weather-index insurance than loss tolerant farmers.

The paper relates to the existing literature in two ways. First, this paper provides a better understanding of the patterns of smallholders' demand for crop insurance in an imperfect market context, which means significant negative opinion has been seen in the market. Following the studies that detected the barriers in the emerging markets of crop insurance, we discussed the patterns of farmers' coverage choices given the presence of resistance to crop insurance due to these barriers. In most cases, the barriers, such as lack of information, knowledge and trust, coexist in emerging markets and affect farmers' insurance decisions at the same time. Under such a circumstance, we find that these barriers not just suppressed farmers' demand for crop insurance, but also formed anomalies in farmers' choices. We also find the low coverage insurance contract seems more marketable than high coverage contract when prevalent negative opinion is observed. However, it is noted that this finding does not suggest that providing low coverage contract is an easy solution to overcome the problems of low demand and anomaly choices. Second, adding to the literature discussing the frameworks to model smallholders' demand for crop insurance, this study shows under certain context, risk averse and loss averse farmers are likely to withhold their demand for crop insurance. The anomaly might undermine the predictive powerful of conventional theory. Last, this paper sheds light on the effectiveness of insurance premium subsidy policy. With the negative opinions seen in emerging markets, it is hard to ensure farmers' equally reap all the benefits of the subsidy solely depending on the market mechanisms.

2.2 LITERATURE REVIEW

In most studies on farmers' insurance decisions, EUT and cumulative prospect theory (CPT) are the two primary frameworks to model farmers' choice for crop insurance, while some studies on index insurance used other utility models (e.g., Elabed and Carter, 2015). The choice of frameworks between EUT and CPT to characterize farmers' insurance decisions depends on the representation of risk preference for the subjects. Although EUT includes varying functional forms, all these functional forms characterize individual risk preference with a single parameter-the degree of risk aversion. The simplification of EUT allows one to explore an individual's behavior with tractable heterogeneity. However, numerous anomalies have been observed in empirical and experimental studies, such as underinsurance or changing choices over the probability of disasters (Du et al., 2016). Starting from the 1970s, Tversky and Kahneman presented a series of studies of CPT to incorporate other heuristic factors in the framework that predict individual choices under risk and uncertainty. Rather than using a single parameter to characterize individual risk preference, CPT captures individual's risk preference with at least four dimensions: the curvature of the value function, loss aversion coefficient, probability weighting and reference point. Under the CPT framework, individuals use reference points to define gains and losses, are more sensitive to the losses than the gains and potentially employ weighted probabilities instead of the actual probability. Supportive evidence of CPT preferences have been found in Harrison et al., (2010) Galarza (2009) and Tanaka et al. (2010), however there is little literature explicitly discussing the effects of those parameters on farmers' coverage choices. Recent exception studies focusing on crop insurance demand using a CPT framework instead of the more traditional EUT framework include Babcock (2015) and Petraud et al. (2015). The former study discusses the application of CPT in explaining the discrepancy of farmers' coverage choices with the predictions by EUT. In particular, Babcock focuses on the choice of reference point and finds that the data of coverage choices by U.S. farmers supports a reference point that treats crop insurance as a stand-alone investment decision. The latter study elicited farmers' risk preference parameters from a series games with smallholder cotton farmers in southern Peru and tests the effectiveness of CPT and EUT in predicting farmers' decision making under risk. The results of Petraud et al (2015) show, somewhat surprisingly, neither framework proved to be particularly powerful in terms of explaining farmers' choices.

Under EUT, more risk averse individuals are likely to pay higher premium loadings for higher level of protection, which means they prefer higher level of coverage given AFP. Recently, suboptimal low coverage choices have been noted and discussed in the U.S. crop insurance market. Du et al. (2016) found that farmers are inclined to turn down a contract with relatively higher risk protection as well as higher subsidy transfer in favor of the contracts with low out-of-pocket premiums. Babcock (2015) examined the application of CPT in explaining the discrepancy of farmers' coverage choices with predictions from EUT. Bulut (2017) discussed budget constraint as one of the possible explanations to this discrepancy and developed a decision-making model based on EUT framework under a binding budget constraint. In developing markets, the negative relationship between risk aversion and insurance choices has been detected. Giné et al. (2008) and Cole et al. (2013) found that less risk averse households were more likely to purchase weather-index insurance in India. Giné et al. (2008) explained the puzzling wrong-signed effect with uncertainty aversion. Specifically, risk averse household hesitated joining in the program due to their imperfect understanding of the product. Clarke (2011) and Hill et al. (2013) found the inverse relationship between risk aversion and take-up of weather-index insurance markets in Ethiopia and suggested the explanation with the models of technology adoption. Hill et al. (2016) showed that a hump-shaped demand curve with respect to risk aversion is expected under the EUT framework given the presence of basis risk and certain amount of premium loadings. Therefore, for both extremely risk averse and risk loving individual the optimal level of indexed cover is expected to be zero.

Building upon these findings, we consider a CPT framework in this study and find evidence that in addition to an anomalous linkage between risk aversion and insurance demand, there is also a significant negative relationship between loss aversion and coverage choice for multi-peril crop insurance (MPCI). Moreover, we also find that loss aversion seems to play a stronger role on farmers' insurance take-up, while risk aversion exerts an effect when individuals face varying coverage levels.

2.3 BACKGROUND ON THE STUDY AREA

In the U.S. crop insurance market farmers have many alternative insurance designs to choose among such as Yield Protection, Revenue Protection, or Revenue Protection with the Harvest Price Exclusion. However in the less mature insurance market of China, MPCI is the primary crop insurance available for small farms. Although MPCI does not cover market risk, there are many advantages of MPCI that fits the environment of developing countries. For instance, MPCI requires less historical data on farm level production, and generates relatively less moral and lower administrative costs compared with revenue insurance. The Chinese government has subsidized the premium since 2007, and the premium rates vary on the region and the underwritten crop. Farmers only need to pay 10-50% of the premium and the maximum indemnity is typically low, 20-50% of the market values of the insured crops or livestock. Thus, farmers potentially suffer great losses even obtaining the full indemnity from an insurance company (Boyd et al. 2011).

Beginning in 2008, the Beijing government started to subsidize MPCI for vegetable growers in the surrounding suburban areas at a high rate, eligible growers only pay 20% of the premium (note: survey data presented later reveals that the majority of farmers are not aware that insurance is subsidized by the government). The maximum indemnity of insurance varies with the type of vegetables, the insured period (half year or a whole year), and production conditions (whether the vegetable is grown in greenhouse or field). Field eggplant, for instance, has a current maximum indemnity per mu[2] of 2200 yuan (around 350 US dollars) for a whole year, and the premium is 5% of the maximum indemnity. Farmers only pay 22 yuan. The payouts are triggered when the loss caused by one or multiple natural disasters exceeds 50% of the potential yield. The amount of actual loss is investigated and estimated by a third party who are often agronomists or meteorologists hired by the government or academic institutions. If the loss occurs in the early growth stage of the vegetable growing cycle, farmers are likely to obtain partial indemnity according to the degree of the damage. The insurance premium for greenhouse

[2] 1 mu ≈ 0.165 acres; 1 mu ≈ 0.067 hectare

vegetable includes the premium for a bundling coverage of the film and structure of the greenhouse. In general, the maximum indemnity is only 30% of the average revenue per mu. A summary of insurance contract information is shown in Appendix I.

2.4 THE DESIGN OF THE EXPERIMENT

We designed three experiments to assess farmer demand and willingness to pay (WTP) for crop insurance and the role of potential negative attitudes towards insurance, risk and loss aversion, and varying coverage levels and subsidy rates. To test for the potential presence of negative opinions by farmers for insurance, we randomly divided farmers into two groups. In one group, hereafter called the Insurance-frame Group, we described the game as an insurance product, while in the other group, hereafter called the Neutral-frame Group, we describe the same game without using any terms of insurance. If farmers have a negative opinion of crop insurance or lack trust in the institution, we would expect farmers in the Insurance-frame group to offer less for an insurance contract than those in Neutral-frame Group. Then, we conducted the risk preference experiment developed by Tanaka, Camerer and Nguyen (2010) to elicit farmers' risk preference. These two experiments involved actual money payment, and the payments were independent and accumulative. The average was approximately 40 yuan, which is equivalent to one third of a day's wage in that area. The minimum possible payment was 4 yuan and the maximum was 537 yuan. Since we did not pay a show-up fee, we compensated 15 yuan to the participants whose payoff was less than this amount. However, we did not give any information about the minimum payment ex-ante. There were only 4 farmers who got less than 15 yuan from the experiments. The third experiment is to observe farmers' coverage choices given high subsidy rates. The design of the experiment is based on the current MPCI program. We provided multiple coverage levels and asked farmers' choice under each.

2.4.1 WTP Experiment

This experiment was aimed to elicit farmers' WTP for hypothesized insurance contracts with three coverage levels, 30%, 60% and 90%. Farmers were presented three tables, one for each coverage level, showing two hypothesized 20-year series of revenue per unit of area in yuan without and with insurance (See Appendix III). The revenue series with insurance does not account for the insurance premium. Therefore, the insured series is first stochastic dominant to the uninsured series. We asked participants that if they had the uninsured revenue, what the maximum price that they were willing to pay to switch from the uninsured revenue series to the insured one. Rather than asking an open-end question, we provided 12 cost options.

For the Insurance-frame Group, in order to make farmers focus on the features of the revenue series we provided instead of on their own farming experience, we chose okra, which is rarely grown in that area, as the underwritten crop being portrayed the game. We assumed that farmers' revenues from growing okra follow a normal distribution with a mean of 15000 and a standard deviation of 5000 yuan. The 20-year revenue streams were drawn from the distribution. The insured revenue in year t was computed as follows:

$$rev_{t,c}^{ins} = max(rev_t, c * \overline{rev}), t = 1,2,\cdots,20$$

Where rev_t represents uninsured revenues in year t (in the right column); c is the coverage level and $c = 30\%$, 60% and 90%; $\overline{rev}$ stands for the sample mean of the uninsured revenues. The 12 price options were varied across coverage levels, taking values from 0% to 180% of the actuarially fair premium in 20% increments. The actuarially fair premium is calculated as follows:

$$\pi_c^f = \frac{1}{20}\sum_{i=1}^{20}(rev_{t,c}^{ins} - rev_t)$$

As mentioned earlier, we split the sample into two groups. In Insurance-frame Group, the participants were explicitly told that they were deciding on a crop insurance product. In Neutral-framed Group, we described the equivalent game in a neutral context. Participants were told they had revenues (Column I) for 20 years. However, they are able to switch the current revenue series to a better revenue series (Column II) by paying some price. Indeed, it was possible for the participants to associate the game with an insurance decision. Only a handful gave indications that they did so. In those cases, we explained to them that this was a research project with no insurance company involved, and we emphasized the rule of payment and that the participants should focus on the features of the game rather than thinking about insurance.

Regarding the experimental protocol, farmers were presented the table and then enumerators verbally described the key features of the revenue series to the farmers such as the values of the mean, the extreme values, the frequency of a covered revenue loss, and the maximum indemnity provided by the insurance contract. The participants were also told that in order to secure the better (insured) revenue series, they had to offer a price that was higher than the one we kept in secret, which was the fair value of the insurance. After the decisions were made, farmers were told whether or not they got the insurance revenue series. If they didn't, a number t from 1 to 20 was drawn and 0.001 of the uninsured revenue at year i was paid to them. If they did, they received 0.001 of the insured revenue at year t minus the price they offered.

A trial game was played before the formal game to familiarize the farmers with the experimental protocol. The trial game included three rounds for each coverage level. All the procedures were the same as in the formal game but the revenue series were different and no payment was won. At the end of the formal game, we used a random incentive device to determine which of the three rounds the payment would be based on, in order to encourage the participants to be mindful of their decisions at all three coverage levels.

2.4.2 Risk Preference Experiment

We assume farmers' behaviors follow CPT. Let x_s represent the outcome s of a prospect, R represent farmer's reference point, $1-\sigma$ represent the curvature of the value function and thus σ is the coefficient of relative risk aversion (CRRA), λ represent the coefficient of loss aversion and α represent the probability weighting. Farmers maximize the prospect function of the following form:

$$EU(p_S, x_S) = \sum_{s=1}^{S} \omega(p_S)\, v(x_S)$$

where

$$v(x_S) = \begin{cases} (x_S - R)^{1-\sigma}, if\ x_S > R \\ 0, if\ x_S = R \\ -\lambda(R - x_S)^{1-\sigma}, if\ x_S < R \end{cases}$$

There are several approaches to define the subjective probability. We follow the commonly used one defined by Prelec (1998). The corresponding subjective probability that an individual perceives is $\omega(p)$:

$$\omega(p) = exp\,\{-(-\,log(p))^{\alpha}\}$$

Following the WTP experiment, participants participate in another experiment to elicit risk preference including the measure of risk aversion (σ), loss aversion (λ) and probability weighting (α). The design of this experiment followed standard TCN procedures.

In the game, we presented farmers three tables (see Appendix II Table 1-2) with a set of pair-wise lotteries in each. The participants decided whether they preferred Lottery A or Lottery B. The enumerators verbally explained the table, pointing out that Lottery A had an unvarying payoff and Lottery B had an increasing payoff down to the list, and that participants were allowed to switch only once at most. We also explained that a random line on the table would be chosen ex-post and the lottery they preferred at that line would be played for actual the game's stake. A trial game with exactly the same procedures, but no payoff, was played to help the participants become familiar with the decision-making process. In the trial, the participants chose a lottery they preferred for each line for each series. Once the switching point or never switching was determined, the enumerator asked participants' their choices for upper and lower options to confirm the answers were consistent. Once the participant felt comfortable she continued with the formal game and make their final choice, the lottery with money payment was played.

A unique combination of CPT parameters (σ, α) can be calculated from each participant's choices in series 1 and 2. The expected utilities of prospect of two lotteries are set to equal at each row. This yields $12\times 14 = 168$ combinations of (σ, α). Based on the estimate of (σ, α), we calculated λ from series 3.

$$\begin{aligned} exp\{-(-ln(0.3))^{\alpha}\} * (15)^{1-\sigma} + (1 - exp\{-(-ln(0.3))^{\alpha}\}) * (5)^{1-\sigma} \\ = exp\{-(-ln(0.1))^{\alpha}\} * (x_1)^{1-\sigma} \\ + (1 - exp\{-(-ln(0.1))^{\alpha}\}) * (2)^{1-\sigma} \end{aligned}$$

$$\begin{aligned} exp\{-(-ln(0.1))^{\alpha}\} * (20)^{1-\sigma} + (1 - exp\{-(-ln(0.9))^{\alpha}\} * (15)^{1-\sigma}) \\ = (1 - exp\{-(-ln(0.3))^{\alpha}\}) * (x_2)^{1-\sigma} \\ + exp\{-(-ln(0.3))^{\alpha}\} * (2)^{1-\sigma} \end{aligned}$$

$$x_3^{1-\sigma} + \lambda * x_4^{1-\sigma} = 18^{1-\sigma} + \lambda * x_4^{1-\sigma}$$

There were 1008 combinations of $(\alpha, \gamma, \lambda)$ in total. The individual's estimates of the three parameters were defined as the midpoint between the switched row and the row above. A switch at the first row was defined as the estimate of switch at the first row, and never switch the estimate of switch at the last row.

2.4.3 Coverage Choice Experiment

The purpose of the third experiment was to observe farmers' choices under a high subsidy rate (80%). Moreover, we are interested in whether the effects of risk preferences on insurance demand would be mitigated by the subsidy or still play a role. The design of the third experiment was practice-based. Currently, MPCI provides a single value of maximum indemnity. The maximum indemnity is roughly equivalent to 30% of the average revenue, commensurate with the nonlabor costs. The low coverage ensures the low premium, which probably is affordable for the majority of the farmers. On the other hand, the risk protection is limited if the maximum indemnity is set at such low level. Thus, we presented farmers a series of hypothesized insurance contracts with varying indemnity values and premiums (See Appendix III), and asked farmers' a "take it or leave it" decision to buy at each level. The subsidy rate was fixed at 80% for all the contracts. The maximum indemnities were equivalent to coverage levels ranging from 10-90% of the average revenue. The calculation of the associated premiums was based on the probabilities of disaster in current MPCI (see Appendix I). One of the questions is seen in Figure 2.1.

2.5 THE DATA

2.5.1 Survey Procedure

The survey was conducted in June and July of 2017 in Shunyi, a northern suburb of Beijing. 477 vegetable farmers were selected at random[3] from 13 villages. The survey was preceded at the meeting rooms of the village administration. The head of village or a staff member from the agricultural extension agency helped to invite vegetable farmers to participate in the study. The recruiter told farmers that 40 yuan on average would be paid as a compensation for participation, but the amount of the payment was based on their decisions in the games and luck.

Each survey was comprised of two sections, questionnaires and experiments. In the survey, an enumerator worked with each participant to aid him or her to fully understand the questions and the protocols of the experiments. The questionnaire was to collect detailed information on individual characteristics, vegetable production, and experiences with disasters and insurance. In the production part, farmers were asked their farmland size for growing vegetables, historical yield, selling prices and various costs for each type of vegetable they grew for profit on average over recent three years. The costs included expenditures on seeds, fertilizers and pesticides, irrigation and maintenance of cropping machines, and depreciation of greenhouse. Most farmers practiced multiple harvests within a year, and the revenue and cost were aggregated on multiple harvests and calculated on an annual basis. In the part of the survey on experiences with disasters and insurance, farmers were asked whether they held insurance contracts or not, the years they purchased insurance, the reasons they did not join in the programs, and their willingness to participate in the insurance. We also asked retrospective questions about disaster experience over the most recent five years, including how many times a disaster

[3] The names of the farmers were roughly selected at random from the directory. However, the households who own relatively large farms and mainly grew vegetable were a certain priority. Only one member from a household was allowed to participate in the survey.

caused over 50% loss and the magnitude of the losses. The questionnaire section usually took 20 to 40 minutes for each participant.

The experiment was played right after the questionnaire section. We conducted the coverage choice experiment first since it was closely related to the MPCI, which had been mentioned in the questionnaire. The design of the experiment was empirical based, and did not contain much framed arrangement. It was relatively easy for farmer to understand the varying coverage levels we provided after finishing the questionnaire.

The WTP experiment and TCN experiment involved real money payments and required practice and experience. In order to make sure participants make decisions based on full understanding of the procedures, we conducted the experiments with multiple steps. First, the enumerators walked through the procedures of each experiment orally with the help of visual aids. Then, a trial round with the same procedures was played to familiarize participants with the procedure. There was no payment in the trial, which was told to participants ex ante. After gaining experience with the experiments, enumerators answered any final questions before proceeding with the formal experiment. The experiment section usually took 60 to 90 minutes for each participant.

2.5.2 Data Description

Table 2.1 shows summary statistics for key variables of interest from the questionnaire. 51% of participants were female. Most completed more than elementary school education (8.9 years) and are about 55 years old. The average farmer in the sample has approximate of 1.038 acres (6.29 mu) on which they grow vegetable and on average farmers grow four types of vegetables on their farm.

2.5.3 The Estimates of Risk Preference Parameters

The descriptive statistics of the parameters are presented in Table 2.2. The mean values for the risk aversion, loss aversion, and probability parameter weighting parameters (σ, α, λ) are (0.27, 0.83, 2.30). Farmers in the study show mild risk aversion (σ is slightly greater than 0), and they seem hold a quite neutral perceived probability of disasters (α is close to 1), while the loss aversion is similar to previous estimation. Different from the farmers in the remote rural area, the farmers in our study live 20 miles from one of the commercialized cities in China. Approximate 29% of the farmers engaged in off-farm works such as transportation, service or business, and 15% of the farmers own automobiles and 78% electric tricycles to get to the closest downtown. All of them own cell phones, and 50% of them use smartphones. These could explain why the farmers in our sample tend to be relatively high risk and loss tolerant on average compared with the samples of the previous studies[4].

2.6 EMPIRICAL RESULTS

2.6.1 Farmers' WTP for Insurance Frame

In the survey, we asked farmers reasons not to buy the current MPCI if they did not. We offered multiple reasons and an unspecific blank. The summary of the cited reasons is presented in Table 2.3. Lack of information or access, poor design of insurance contract and concerns on low quality of service were the top three reasons. Many of them expressed their concerns orally or by filling in the open-ended question, saying they held conservative opinions toward insurance even if they had an easy access.

[4] TCN found (0.59, 0.74, 2.59) for their samples in Vietnam, (Tanaka et al., 2010) and Liu found (0.49, 0.69, 3.47) for a sample of Chinese farmers (Liu, 2013)

In WTP experiment, we collected farmers' WTP for hypothesized insurance contracts with coverage level 30%, 60% and 90%. Farmers' answers were translated into the percent of the AFP at each coverage level. For example, if a farmer chose "B" for the coverage 30%, his outcome variable (WTP relative to AFP, and hereafter relative WTP for short) is recorded as 0.2. We divided the WTP experiment into two groups to test and measure potential negative opinions, which is reflected by the effect of insurance frame. We randomly selected 7 out of 13 villages for the Insurance-frame Group, where the game was described as an insurance contract. The rest of the villages were the Neutral-frame group, where the game was described in a general context. Figure 2.2 illustrates the differences in the smoothed empirical cumulative distribution function (CDF) of the relative WTP by group. The curve of Neutral-frame Group is lower than the Insurance-frame Group and a considerable gap can be seen between them, indicating that farmers tend to offer lower prices for an insurance contract than a neutral contract.

Since we randomized at village level instead of individual level, it is likely that demographics and economic differences between villages may jeopardize the randomization between the grouping. Table 2.4 reports the comparison between two groups. We observed that some variables were significantly different between the two treatments based on the results of a set of t-tests. In order to mitigate the shortfall of the incomplete randomization, we include all the related variables in the OLS regression framework as follows.

$$WTP_i = \beta * frame_i + {X_i}^T\gamma + \varepsilon_i$$

where WTP_i represents the relative WTP offered by i^{th} participant, $frame_i$ is a dummy variable indicating whether she is assigned in Insurance-frame Group. X_i is a vector of other covariates, and ε_i random variables with expected values equal to 0, and we allow the correlation within village.

Table 2.5 reports the results of insurance frame regression. Column (1) shows that the insurance frame is negatively associated with participants' WTP by 18.5%. If participants' characteristics variables are considered, the difference reduces to 16.1% but still significant at 5%. The estimates imply that on average, farmers place over 15% less value for an insurance contract than an equivalent contract without the name of insurance.

Furthermore, we compare the effects of insurance frame across different coverage levels. Figure 2.3 reports the empirical cumulative distribution function of the relative WTP by group under each coverage level. Under each coverage level, farmers in Insurance-frame Group always offer less relative price than those in Neutral-frame Group. The gap in relative WTP between two groups is not salient for 30% coverage, and it becomes significant for 60% and 90% coverage. We run OLS regression of relative WTP on the insurance frame and covariates at each coverage level as follows:

$$WTP\_c_i = \beta * frame\_c_i + {X_i}^T\gamma + \varepsilon\_c_i$$

where c represents coverage level and $c =$ 30%, 60% and 90%. $frame\_c_i$ is a dummy variable indicating whether she is assigned in Insurance-frame Group. X_i is a vector of other covariates, and ε_i random variables with expected values equal to 0, and we allow the correlation within village.

Table 2.6 reports the results that are consistent with the trend we find in Figure 2.3. The negative association of insurance frame rises from -6% to -21% of AFP with the coverage increases from 30% to 90%. The results imply that farmers are more resistant to the name of insurance when they face high coverage contract.

2.6.2 Farmers' Choice for Coverage Levels

We found two types of anomalies in farmers' choices regarding coverage levels. First, farmers value the low coverage higher than high coverage. Second, risk aversion and loss aversion farmers have negative association with WTP and this association increases with coverage level.

Figure 2.4 presents the histograms of relative WTP over three coverage levels. Farmers are willing to offer higher prices for low-coverage insurance than for high-coverage and this tendency is more pronounced among the farmers in Insurance-frame Group. We use stacked OLS regression to compare the effects of coverage levels on farmers' decision.

$$WTP_i = (Coverage)^T\beta + {X_i}^T\gamma + \varepsilon_i$$

where $Coverage$ specifies the indicators for each coverage levels. X_i is a vector of other covariates, and ε_i random variables with expected values equal to 0, and we allow the correlation within village.

Table 2.7 reports the regression result. The significantly negative coefficients (p-values of 0.021 and 0.023 for the 60% and 90%, respectively) of coverage indicators suggest that comparing with the relative prices for 30% coverage, farmers are willing to pay 21% less for 60% coverage and 27% less for 90% coverage with other things equal.

In rational theory, risk averse and loss averse individuals should have higher willingness to seek risk protection and thus purchase insurance than risk loving and loss tolerant individuals. By contrast, according to the regression results below, we find that the risk aversion and loss aversion have significant negative association with WTP for insurance in our data. Moreover, the negative effects become even more significant for the high coverage level. We run OLS regressions on each coverage level separately, at each c level as follows.

$$WTP\_c_i = Z_i{}^T\beta + X_i{}^T\gamma + \varepsilon\_c_i$$

where WTP_c_i represents the relative WTP offered by participant i, Z_i is the vector of risk preference parameters including $(\sigma_i, \lambda_i, \alpha_i)$. X_i is a vector of other covariates, and ε_i random variables with expected values equal to 0, and we allow the correlation within village.

The results are seen in Table 2.8. Negative coefficients of risk aversion and loss aversion are seen at each coverage level. A clear trend can be seen that the effects of loss aversion increase with coverage, from -0.021 for 30% to -0.031 for 90%. Although not as significant as loss aversion, risk aversion has the negative signs for all coverage levels as well (-0.042, -0.107, -0.102 for 30%, 60%, 90% respectively). This leads us to conclude that the inverse effects of risk aversion and loss aversion increase with coverage and the inverse effects increase when farmers are facing high coverage. This result may indicate that farmers perceive high coverage levels as an additional source of risk rather than a type of protection.

2.6.3 Robustness Check and the Effect of Premium Subsidy

To test whether the anomalous choices are robust as well as to assess whether high subsidies might mitigate the anomalies regarding farmers' choice on coverage level and risk preference, we examine farmers' choice for Coverage Choice Experiment. Recall that in the Coverage Choice Experiment, we asked farmers' buy-or-not buy decisions for the coverage levels from 20-90% with an 80% premium subsidy. It is important to note that the subsidy rate was fixed at 80%. Thus, the highest coverage provides farmers the most monetary transfer in expectation, and therefore leads the highest expected utility level. Figure 2.5 reports the percentages of “buy” decisions over varying coverage levels. Still, even with the 80% subsidy rate, take-up rate for the lowest coverage is still 25% higher than the highest coverage, which means the high subsidy rate has limited impact to mitigate the anomaly choices regarding coverage levels. Similar to the finding in Du et al (2015), our data also reveals that farmers are likely to turn down the contracts that provide high transferring benefits and settle for low level of risk protection.

The anomalous choices regarding risk preference were also seen given a high subsidy rate. In order to measure the association between coverage choice and risk preference parameters, we use interval regression to model farmers’ coverage decisions that have interval censoring. We translate farmers’ choice for each coverage level into the intervals farmers are willing to accept. For example, if a farmer would like to purchase from 20% coverage and stop purchasing at 70% (see Figure 2.6), her outcome variable is represented as an interval “2 to 7”. If a farmer answered “buy” once, for insurance at 30% coverage, and rejected all the other contracts, her outcome variable is “3 to 3”.

The regression is specified as follows:

$$Coverage\ interval_i = {Z_i}^T \beta + {X_i}^T \gamma + \varepsilon_i$$

where $Coverage\ interval_i$ represents the coverage interval preferred by participant i; Z_i is the vector of risk preference parameters including $(\sigma_i, \lambda_i, \alpha_i)$. X_i is a vector of other covariates, and ε_i random variables with expected values equal to 0, and we allow the correlation within village. Table 2.9 reports results. We can see that the anomaly effects of risk preference still linger given that the inverse associations of risk preference parameters are still significant.

2.7 DISCUSSIONS AND CONCLUSION

Using data from a set of field experiments with 477 vegetable farmers in China, we found evidence that farmers are resistant to insurance frame contract and thus place considerably less value than an equivalent contract without the name of insurance. The negative insurance-name effect can be considered as a measure of farmers' negative opinions. The causes of the negative opinions include lack of trust, information, or insurance knowledge, or exterior deficiency such as pool quality of contract design or high transaction cost, which had been detected in previous literature. Under such imperfect market environment, there are significant anomalies in farmers' insurance decisions regarding coverage level. There are three types of anomalies in our data: First, farmers place a less value for an insurance contract than for an equivalent risk-reducing contract described in a neutral frame. Moreover, farmers tend to be more willing to purchase low coverage than high coverage, even when the high coverage provides higher value of money transferring from government-like institutions. Third, risk averse and loss averse farmers who are theoretically supposed to be more interested in adopting risk protection tools show less willingness to purchase high coverage insurance. Under the imperfect market conditions, CPT may potentially provide a more reliable tool to analyze smallholder farmers' decisions since it includes multiple dimensions of risk preferences. However, given the context of farmers' intrinsic resistance to crop insurance program, the predictability of both theories might be undermined by the existence of the anomalies.

The findings carry three policy implications. One is that when the market is not perfectly developed, anomalies are usually seen in various aspects apart from low insurance take-up rate. The distortions in choices for crop insurance seems lessen when farmers are facing with low coverage insurance. However, this finding does not simply suggest that providing only low coverage insurance ensures a relatively high take-up. In practice, low coverage insurance might reinforce farmers' negative opinions in the regarding that the risk protection provided by the contract is limited. Moreover, we find that providing high subsidy seems not a panacea to the problem of lack of crop insurance take-up. In fact, crop insurance subsidies are not equitably distributed across farmers. Those farmers with high risk aversion and loss aversion may not reap as much the benefits of the subsidy as do their peers with low risk aversion and loss aversion. This inequality might even intensify wealth inequality among smallholder farmers in rural areas, given the findings that risk averse and loss averse farmers are slow to adopt new technology in previous studies (Liu, 2009; Tanaka et al., 2010). Last, the results of this study imply that the negative opinions toward crop insurance program could result in farmers' undervalue of insurance contract. To maintain the sustainability of the insurance program, in spite of premium subsidy, it is critical to provide information and knowledge and establish trust among farmers. Local institutions, such as agricultural extensions, may relieve the negative association of insurance-name by helping farmers negotiate in the claims and better understand the function of insurance.

Table 2.1 Summary Statistics of Farmers' Characteristics

Variable	Mean	Std. Dev.	Min	Max
Gender	0.51	0.50	0	1
Age	55.35	7.07	26	75
Years of education	8.89	2.37	3	18
Total vegetable area planted (mu)	6.29	3.22	0.3	26
Number of vegetable planted	3.15	1.19	1	8
Years of growing vegetable	36.00	15.46	1	61
Revenue per mu (yuan)	5405	2641	300	15075
Net profit per mu	2600	2796	-5841	13784
Times of disasters in recent 5 years	1.04	1.19	0	5
Percent of other income	0.16	0.29	0	0.9

Table 2.2 Summary Statistics of Risk Preference

Variable	Mean	Std. Dev.	Min	Max
Risk aversion (σ)	0.265	0.510	-0.501	0.883
Loss aversion (λ)	2.648	2.434	0.296	13.512
Probability weighting (γ)	0.831	0.390	0.165	1.535

Table 2.3 Self-Reported Reasons Not to Purchase the Current MPCI

Reason	Number	Percent*
Reason about the insurance contract		
High premium	21	4.4%
Low payout	50	10.5%
Low quality of service**	73	15.3%
Reason about the household characteristics		
The probability of disasters is low	42	8.8%
Have other ways to cope with risk	26	5.5%
No one purchases in the network	6	1.3%
No access or information	214	44.9%

* The percent cited reasons of the total number of participants (477). We allowed farmers to choose multiple reasons.

** Low quality of services includes a tedious procedure to make a claim and receive the payouts, and lower payout than expectation.

Table 2.4 Comparisons of Statistics between Two Groups

	Mean (Neutral)	Mean (Insurance)	Diff.	Standard Err.
Risk aversion (σ)	0.300	0.231	0.070	0.047
Loss aversion (λ)	2.673	2.624	0.050	0.223
Probability weighting (α)	0.825	0.836	-0.011	0.036
Gender (F=1)	0.515	0.496	0.019	0.046
Age	54.6	56.1	-1.5	0.64**
Years of education*	9.026	8.756	0.270	0.217
Rev. per unit (yuan)	5905	4936	969	238***
Cost per unit (yuan)	3163	2470	693	129***
Net prof. per unit (yuan)	2742	2466	276	256***
Vege. area planted (Mu)	6.875	5.746	1.129	0.291
N	231	246	-	-

*Years of education takes the values of 3, 6, 9, 12 or 18, indicating primary school dropout, primary school education, middle school education, high school education and college education. Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0$.

Table 2.5 OLS Regression of Relative WTP on Insurance Frame

	(1)	(2)
Frame (Insurance =1)	-0.185***	-0.161**
	(0.071)	(0.073)
Total vegetable area planted (mu)		-0.003
		(0.005)
Revenue (1000 yuan/mu)		0.021**
		(0.009)
Gender		0.094**
		(0.047)
Age		-0.003
		(0.005)
Years of education		0.007
		(0.010)
Constant	0.956***	0.885**
	(0.053)	(0.369)
Observations	1431	1431
R^2	0.029	0.049

Note: Bootstrapped standard errors are clustered at the village level. The dependent variables are the relative WTP and the explanatory variable labels (in order) denote total vegetable area planted in mu, calculated vegetable revenue in yuan/mu based on respondents' price, yield, and acreage, times of harvest within a year and so on, dummy variables of insurance frame, gender=female, age, years of education (takes the values of 3, 6, 9, 12 or 18).
Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table 2.6 OLS Regression of Relative WTP on Insurance Frame at Each Coverage Level

	(1)	(2)	(3)	(4)	(5)	(6)
	30%	60%	90%	30%	60%	90%
Frame	-0.100	-0.226***	-0.231***	-0.064	-0.207**	-0.211**
(Insurance =1)	(0.064)	(0.071)	(0.085)	(0.066)	(0.075)	(0.083)
Total vegetable				0.001	-0.004	-0.005
area planted (mu)				(0.007)	(0.006)	(0.007)
Revenue (1000				0.023***	0.017	0.021**
yuan/mu)				(0.009)	(0.011)	(0.010)
Gender				0.075	0.119**	0.088
				(0.046)	(0.058)	(0.056)
Age				-0.007*	-0.000	-0.001
				(0.004)	(0.006)	(0.005)
Years of education				0.004	0.012	0.006
				(0.010)	(0.010)	(0.013)
Constant	0.875***	0.726***	0.666***	1.017***	0.504	0.535
	(0.046)	(0.053)	(0.063)	(0.298)	(0.444)	(0.394)
Observations	477	477	477	477	477	477
R^2	0.009	0.043	0.052	0.039	0.063	0.072

Note: Bootstrapped standard errors are clustered at the village level. The dependent variables are the relative WTP and the explanatory variable labels (in order) denote total vegetable area planted in mu, calculated vegetable revenue in yuan/mu based on respondents' price, yield, and acreage, times of harvest within a year and so on, dummy variables of insurance frame, gender=female, age, years of education (takes the values of 3, 6, 9, 12 or 18).
Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table 2.7 OLS of Relative WTP on Coverage Levels

	(1)	(2)
Coverage level=60%	-0.215***	-0.215***
	(0.021)	(0.021)
Coverage level=90%	-0.277***	-0.277***
	(0.023)	(0.023)
Total vegetable area planted		0.001
(mu)		(0.007)
Revenue (1000 yuan/mu)		0.025**
		(0.011)
Gender		0.101*
		(0.052)
Age		-0.003
		(0.005)
Years of education		0.007
		(0.010)
Constant	1.024***	0.944***
	(0.034)	(0.351)
Observations	1431	1431
R^2	0.081	0.120

Note: Bootstrapped standard errors are clustered at the village level. The dependent variables are the relative WTP and the explanatory variable labels (in order) denote total vegetable area planted in mu, calculated vegetable revenue in yuan/mu based on respondents' price, yield, and acreage, times of harvest within a year and so on, dummy variables of insurance frame, gender=female, age, years of education (takes the values of 3, 6, 9, 12 or 18).
Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table 2.8 OLS Regression of Relative WTP on Risk Preference Parameters

	(1) 30%	(2) 60%	(3) 90%	(4) 30%	(5) 60%	(6) 90%
Risk aversion (σ)	-0.042	-0.107*	-0.102*	-0.057	-0.123*	-0.119**
	(0.057)	(0.058)	(0.055)	(0.061)	(0.063)	(0.059)
Loss aversion (λ)	-0.021*	-0.025**	-0.031***	-0.020**	-0.024*	-0.031***
	(0.011)	(0.011)	(0.010)	(0.009)	(0.013)	(0.011)
Probability	0.138**	0.102	0.063	0.120**	0.084	0.044
weighting (α)	(0.067)	(0.070)	(0.061)	(0.048)	(0.052)	(0.062)
Total vegetable				0.004	0.002	0.001
area planted (mu)				(0.008)	(0.008)	(0.009)
Revenue (1000				0.023***	0.023*	0.026**
yuan/mu)				(0.009)	(0.013)	(0.013)
Gender				0.081*	0.133**	0.102*
				(0.045)	(0.061)	(0.062)
Age				-0.007*	-0.001	-0.001
				(0.004)	(0.006)	(0.005)
Years of education				0.002	0.010	0.004
				(0.010)	(0.010)	(0.012)
Constant	0.775***	0.619***	0.605***	0.949***	0.377	0.465
	(0.077)	(0.080)	(0.073)	(0.292)	(0.433)	(0.384)
Observations	477	477	477	477	477	477
R^2	0.018	0.020	0.023	0.051	0.048	0.052

Note: Bootstrapped standard errors are clustered at the village level. The dependent variables are the relative WTP. Risk aversion (CRRA) takes value (-1, 1). We allow farmers to be risk loving in the design of TCN game. A farmer whose risk aversion less than 0 means she is risk loving. Loss aversion (λ) takes value from 0 to 14. Probability weighting (α) takes value (0, 1.5). Covariates include total vegetable area planted in mu, calculated vegetable revenue in yuan/mu based on respondents' price, yield, and acreage, times of harvest within a year and so on, dummy variables of insurance frame, gender=female, age, years of education (takes the values of 3, 6, 9, 12 or 18). Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table 2.9 Interval Regression of Coverage Choice under High Subsidy

	(1)	(2)
Risk aversion (σ)	-0.383***	-0.393***
	(0.134)	(0.120)
Loss aversion (λ)	-0.091**	-0.080**
	(0.036)	(0.035)
Probability weighting (α)	-0.031	-0.087
	(0.283)	(0.260)
Total vegetable area		-0.024
planted (mu)		(0.025)
Revenue (1000 yuan/mu)		0.026
		(0.042)
Gender		0.095
		(0.224)
Age		-0.033*
		(0.019)
Years of education		0.061
		(0.045)
Constant	2.766***	4.021***
	(0.384)	(1.330)
Ln(sigma) Constant	0.476***	0.456***
	(0.140)	(0.134)
Observations	477	477

Note: Bootstrapped standard errors are clustered at the village level. The dependent variables are the intervals of farmers' coverage choices. Risk aversion (CRRA) takes value (-1, 1). We allow farmers to be risk loving in the design of TCN game. A farmer whose risk aversion less than 0 means she is risk loving. Loss aversion (λ) takes value from 0 to 14. Probability weighting (α) takes value (0, 1.5). Covariates include total vegetable area planted in mu, calculated vegetable revenue in yuan/mu based on respondents' price, yield, and acreage, times of harvest within a year and so on, dummy variables of insurance frame, gender=female, age, years of education (takes the values of 3, 6, 9, 12 or 18).

Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Maximum indemnity (Yuan)	Premium (Yuan)	Buy or not
5000*	100	□ Yes □ No

* 5000 yuan is approximately equivalent to 50% coverage level on average.

Figure 2.1 An Example of Coverage Choice Experiment

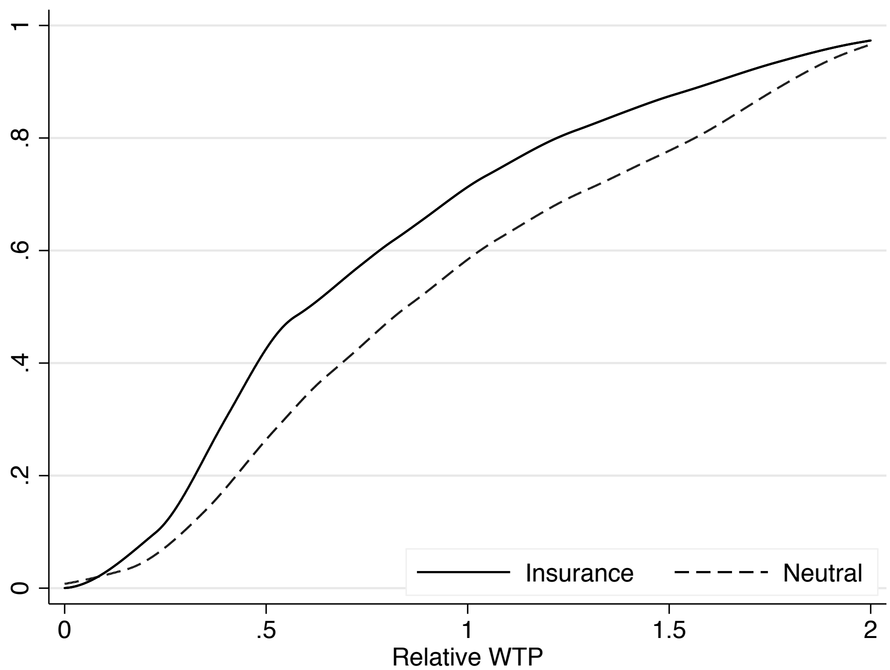

Figure 2.2 Smoothed Empirical CDF of the Relative WTP by Group

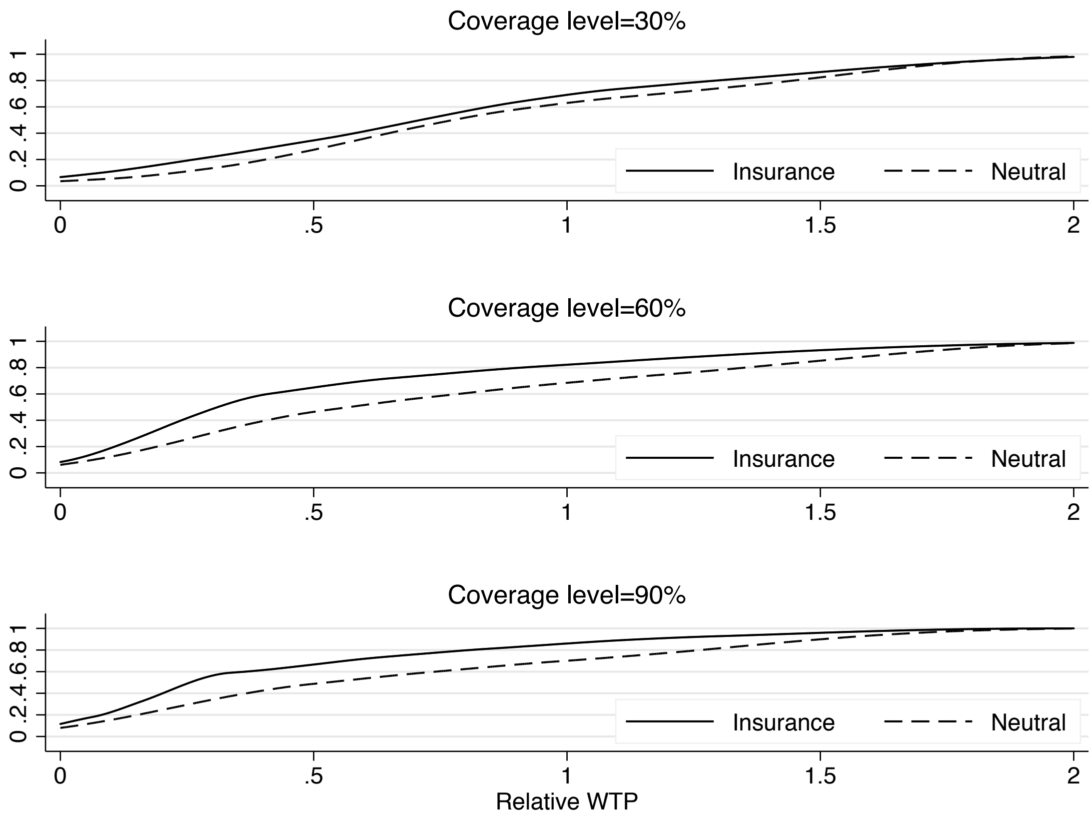

Figure 2.3 Smoothed Empirical CDF of the Relative WTP under Each Coverage Level

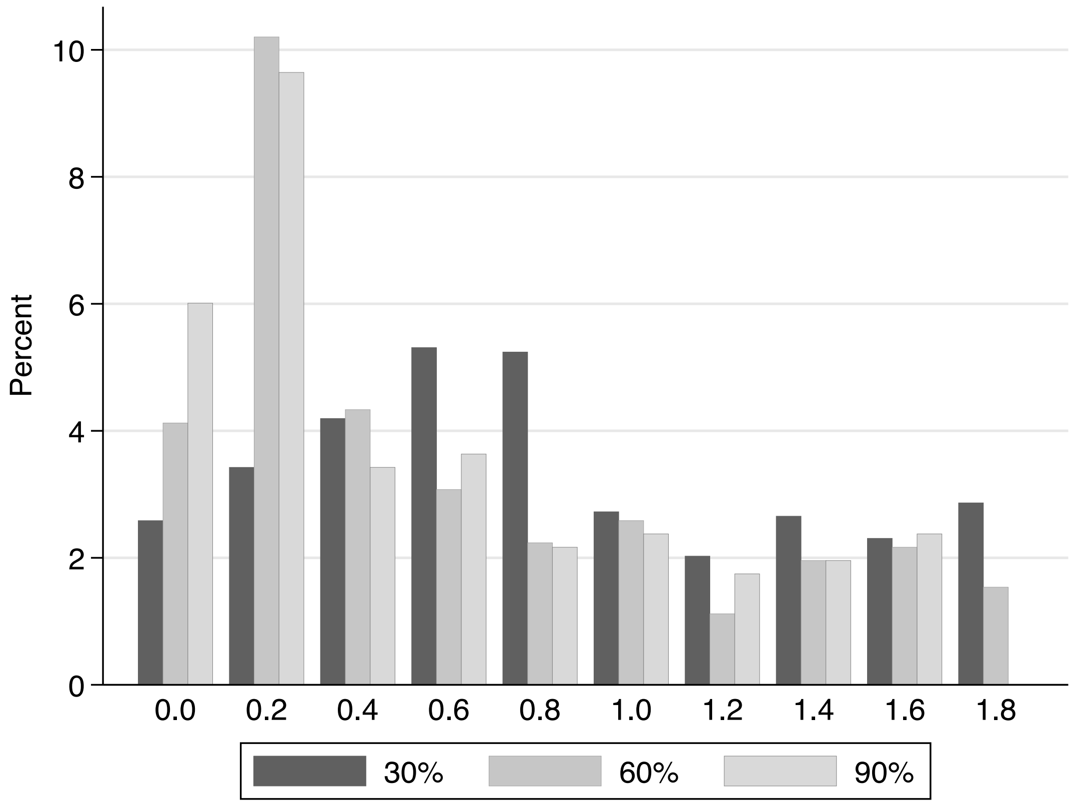

Figure 2.4 The Histograms of Relative WTP over Three Coverage Levels

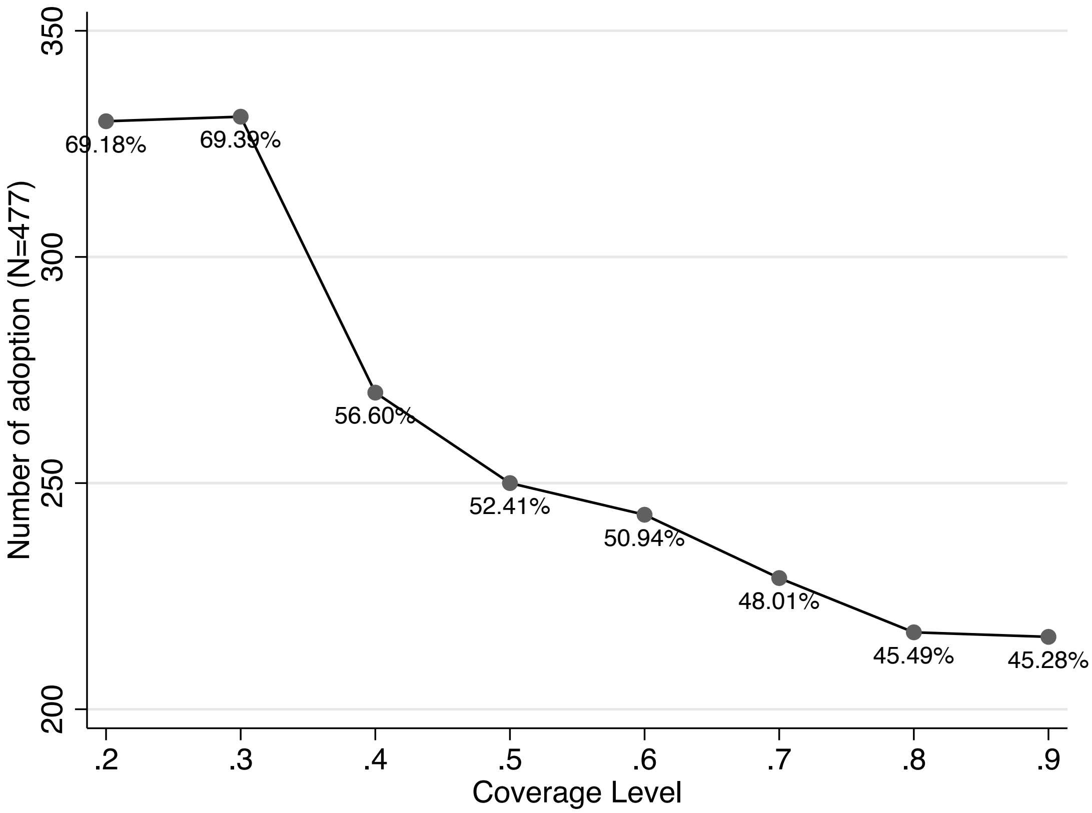

Figure 2.5 Farmers' Take-up Rate for Each Coverage with 80% Premium Subsidy

Coverage level	20%	30%	40%	…	70%	80%	90%
Choice	No	Yes	Yes	Yes	Yes	No	No

Figure 2.6 An Example of the Specification of The Outcome Variable in Interval Regression

BIBLIOGRAPHY

Babcock, B.A., 2015. Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice. *American Journal of Agricultural Economics*, 97(5), pp.1371-1384.

Barnett, B.J., Barrett, C.B. and Skees, J.R., 2008. Poverty Traps and Index-Based Risk Transfer Products. *World Development,* 36(10), pp.1766-1785.

Boyd, M., Pai, J., Qiao, Z. and Ke, W., 2011. Crop Insurance Principles and Risk Implications for China. *Human and Ecological Risk Assessment,* 17(3), pp.554-565.

Bulut, H., Collins, K.J. and Zacharias, T.P., 2012. Optimal Coverage Level Choice with Individual and Area Insurance Plans. *American Journal of Agricultural Economics,* 94(4), pp.1013-1023.

Cai, J. and Song, C., 2017. Do Disaster Experience and Knowledge Affect Insurance Take-up Decisions?. *Journal of Development Economics,* 124, pp.83-94.

Clarke, D.J., 2011. A Theory of Rational Demand for Index Insurance. *Economics Series Working Papers,* 572.

Cole, S., Sampson, T. and Zia, B., 2011. Prices or Knowledge? What Drives Demand for Financial Services in Emerging Markets? *The Journal of Finance,* 66(6), pp.1933-1967.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J., 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics,* 5(1), pp.104-35.

Du, X., Feng, H. and Hennessy, D.A., 2016. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics,* 99(3), pp.732-756.

Elabed, G. and Carter, M.R., 2015. Compound-risk aversion, Ambiguity and the

Willingness to Pay for Microinsurance. *Journal of Economic Behavior & Organization,* 118, pp.150-166.

Galarza, F., 2009. Choices under Risk in Rural Peru. *University of Wisconsin-Madisson.*

Gaurav, S., Cole, S. and Tobacman, J., 2011. Marketing Complex Financial Products in Emerging Markets: Evidence from Rainfall Insurance in India. *Journal of Marketing Research,* 48(SPL), pp.S150-S162.

Giné, X. and Yang, D., 2009. Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi. *Journal of Development Economics,* 89(1), pp.1-11.

Giné, X., Townsend, R. and Vickery, J., 2008. Patterns of Rainfall Insurance Participation in Rural India. *The World Bank Economic Review*, 22(3), pp.539-566.

Harrison, G.W., Humphrey, S.J. and Verschoor, A., 2009. Choice under Uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal,* 120(543), pp.80-104.

Harrison, G.W., List, J.A. and Towe, C., 2007. Naturally Occurring Preferences and Exogenous Laboratory Experiments: A Case Study of Risk Aversion. *Econometrica,* 75(2), pp.433-458.

Hill, R.V., Hoddinott, J. and Kumar, N., 2013. Adoption of Weather Index Insurance: Learning from Willingness to Pay among a Panel of Households in Rural Ethiopia. *Agricultural Economics,* 44(4-5), pp.385-398.

Hill, R.V., Robles, M. and Ceballos, F., 2016. Demand for a Simple Weather Insurance Product in India: Theory and Evidence. *American Journal of Agricultural Economics,* 98(4), pp.1250-1270.

Kahneman, D. and Tversky, A., 2013. Prospect Theory: an Analysis of Decision under Risk. *In Handbook of the Fundamentals of Financial Decision Making: Part I* (pp. 99-127).

Kahneman, D., Knetsch, J.L. and Thaler, R.H., 1991. Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives,* 5(1), pp.193-206.

Kunreuther, H. and Pauly, M., 2004. Neglecting Disaster: Why Don't People Insure against Large Losses?. *Journal of Risk and Uncertainty,* 28(1), pp.5-21.

Liu, E.M., 2013. Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers In China. *Review of Economics and Statistics,* 95(4), pp.1386-1403.

Petraud, J., Boucher, S. and Carter, M., 2015. Competing Theories of Risk Preferences and The Demand for Crop Insurance: Experimental Evidence from Peru (No. 1008-2016-80041). Tanaka, T., C.F. Camerer, and Q. Nguyen. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100 (1): 557–71

Quiggin, J., 1991. Comparative Statics for Rank-dependent Expected Utility Theory. *Journal of Risk and Uncertainty,* 4(4), pp.339-350.

Tanaka, T., Camerer, C.F. and Nguyen, Q., 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review,* 100(1), pp.557-71.

CHAPTER 3

PROSPECT THEORY, NARROW FRAME AND INSURANCE DEMAND

Abstract

Building upon the findings in Chapter 2, the second essay reconciles these anomalies within a prospect theory framework under narrow framing. Recognizing that smallholder farmers in rural areas of developing countries may have less experience with crop insurance and less trust in the institutions managing crop insurance, this study suggests that farmers may tend to view crop insurance as an innovative technology rather than a risk-transferring tool. In other word, the payoff of crop insurance is not seen as related to their crop revenue or crop risk. Instead, it is seen as independent investment decision. Under such assumption, paying premium without receiving any indemnity in a good harvest year is evaluated as a loss, which brings disutility. The disutility from loss is even amplified through the coefficient of loss aversion. Empirical tests indicate support for this conjecture.

3.1 INTRODUCTION

Crop insurance provision to the poor could play an important role in a comprehensive system of protection against risk of natural disaster for small farms in developing countries (Hazell 1992; Giné et al. 2009). Over the past 25 years, agricultural insurance programs have been heavily subsidized by the government sector not just in developed countries, but in important emerging markets as well. An often-cited impetus for the government to subsidize crop insurance programs is that the subsidy is treated as one of the so-called green box policies and excluded from WTO reduction commitments. However, many of crop insurance programs in developing countries have not lived up to their expectations to protect the small farm from risk due to unexpectedly low take-up rate, even under high premium subsidy (Cole et al., 2013; Giné et al., 2008; Boucher and Mullally, 2010). In another word, smallholder farmers who are target of subsidy policy leave the subsidy benefits on the table. A large body of literature discusses farmers' anomalous choice for the crop insurance, and the proposed explanations include poor contract design, farmers' insufficient financial literacy, lack of knowledge and experience of disasters and so on (Gaurav et al., 2011; Cole et al., 2013; Cai et al., 2015). Similar anomalous choices are also discussed in Chapter 2. The objective of this study is to test whether these anomalous findings reconciles within a prospect theory framework under narrow framing.

The fundamental theoretical framework of farmers' insurance behavior was expected utility theory, before the competing framework prospect theory was proposed by Kahneman and Tversky (1979, 1992). Under the framework of the expected utility theory, numerous anomalies of the expected theory have been found in the data from experiment settings and the real world. For instance, the expected utility theory predicts that demand for an actuarially fair insurance contract should increase with the degree of risk aversion (Mossin, 1968; Clarke, 2010). However, empirical studies have shown that demand for insurance may consistently decrease with risk aversion of subjects (Giné et al., 2008; Cole et al., 2013; Hill et al., 2013). Moreover, the expected utility theory suggests that in face of insurance subsidized by the government, a risk averse individual will pursuit high coverage in order to obtain high level of risk protection and high money transferring benefits. In contrast, considerably suboptimal low coverage choices have been noted and discussed in the U.S. crop insurance market (Du et al., 2016; Babcock, 2015; Bulut, 2016).

Recently, many studies on crop insurance depart from the conventional expected utility framework. Elabed and Carter (2015) discussed the application of ambiguity aversion utility (KKK model) to explain farmers' suboptimal choices in face of basis risk of index insurance. Petraud at el (2015) discussed the effectiveness of prospect theory and expected utility theory in predicting farmers' decision making under risk. Many studies also find supportive evidence of CPT preferences in Africa, Latin America and Asia (Harrison et al., 2010; Galarza 2009; Tanaka et al., 2010).

This paper takes a lens of behavioral economics to provide explanations to small farms' anomalous insurance choices disclosed from a series of surveys and economic experiments with 477 vegetable farmers in China. These anomalies are in line with several prior studies on crop insurance demand in developing countries. Taken together, the experimental results in this paper can be summaries as follows: first, a risk averse individual is less likely to purchase insurance; second, a loss averse individual is less likely to purchase insurance; third, low coverage insurance contracts tend to be more salable than high coverage insurance. These results, which are viewed as anomalies under expected utility theory framework, can be explained by prospect theory under narrow framing assumption. Narrow framing describes the phenomenon people often evaluate a lottery in isolation, separately from other risks. If a farmer frames crop insurance narrowly, she will treat crop insurance as an investment independent from her overall wealth or crop revenue. Narrow framing is closely related to the concept of reference point. Under narrow framing assumption, the reference point to make insurance decision is status quo with zero insurance. Indeed, the narrow framing assumption may be at odds with the purpose of buying insurance, which is to alleviate the impact of income losses. However, as psychologists have noted, many people fail to account for other risks they also face, particularly when making complex decisions (Tversky and Kahneman, 1981; Kahneman and Lovallo, 1993; and Read et al., 1999). In the case of crop insurance in an emerging country, partial reason for narrow framing is that the farmers in rural areas usually have little experience in purchasing any types of insurance. Therefore they are likely to view crop insurance as an innovative technology rather than a risk-transferring tool. Moreover, trust issues, lack of insurance knowledge and incomplete information affects farmers' choices. Under the imperfect market conditions, farmers are likely to hold a conservative opinion toward crop insurance. The findings of this study stress that in an emerging crop insurance market, where purchasing insurance is not commonplace, farmers' behavior is likely to depart from the conventional assumptions of rationality.

The following paper is structured as follows. Section 2 reviews the related literature. Section 3 provides the theoretical framework and derived implication from the framework. Section 4 presents the experiments and data followed by Section 5, which presents the regression model and the results. Section 6 discusses the policy implication and concludes the paper.

3.2 LITERATURE REVIEW

Kahneman and Tversky originally motivated prospect theory in 1979 and developed in 1992. Different from expected utility theory using a single parameter to capture individual's risk preference, prospect theory incorporates four parameters of risk preference: reference point, risk aversion, loss aversion and probability weighting (See Figure 3.1). The reference point serves as a cutting point that divides the outcomes of a lottery into the domains of gain and loss. An individual evaluates the lottery based on the value of gains and losses relative to the reference point. Moreover, prospect theory also assumes most people are risk aversion, which also implies their sensitivity to gains/losses exhibits a diminishing trend. The law of diminishing sensitivity gives the value function an S-shape-concave above the reference point and convex below it. Third, for most people, the sensitivity to losses is usually larger than the same amount of gains. Lastly, instead of objective probabilities, subjective probabilities are used to calculate the value of the lottery. Furthermore, different from traditional utility theory, which assumes individual considers her total wealth while evaluating a lottery, Kahneman and Lovallo, (1993) argues that she tends to frame a lottery in isolation, rather than mixing it with her pre-existing risks. They suggest that people often choose a narrow frame when making decisions under risk. In other words, individual acts as if she gets utility directly from the outcome of the lottery, even if the lottery is just one of many that determine her overall wealth risk. The behavioral features of prospect theory make it a promising framework in explaining farmers' choices under risk.

Before the wide application of the prospect theory, most studies that investigate demand for insurance assume farmers' behavior is consistent with expected utility model. However, under-insurance and over-insurance are often observed in a variety of insurance markets. For example, Sydnor (2010) finds that households strongly prefer low deductibles in terms of homeowners insurance, which indicates triple digit relative risk aversion. Cohen and Einav (2007) find extremely under-insurance behavior in the deductibles selection of auto insurance.

Recent studies reveal the evidence of anomalies regarding farmers' coverage choice in US crop insurance. Date back to 1938 crop insurance programs have been highly subsidized in US. A recent objective of crop insurance program is to induce farmers to choose high coverage crop insurance in order to eliminate the demand for ad hoc disaster assistant programs. Under expected utility theory framework, farmers will buy insurance coverage as high as the level that maximizes the per-acre subsidies (Babcock 2015). However, Du et al (2016) found that farmers prefer contracts that transfer less subsidy and retain more risk and turn down contracts that transfer comparatively more subsidy and retain less risk. Babcock (2015) explains the anomaly discussed in Du et al. with the prospect theory framework. Moreover, he found that farmers are likely to choose a narrow frame and view insurance as a stand-alone investment tool. However, he used aggregated data, which does not allow him to provide information on the association between risk preference parameters and insurance coverage choice.

In developing markets, the inverse relationship between risk aversion and insurance choices has been detected in several studies. Giné et al. (2008) explore the rainfall insurance take-up offered to smallholder farmers in rural India. They document the puzzling phenomenon that risk-averse households are less likely to purchase the insurance. A possible explanation they provide is farmers' unfamiliarity with the innovative insurance product. Cole et al. (2013) use a series of randomized field experiments in rural India to investigate the factors in the adoption of the rainfall insurance and also find the same trend. Hill (2013) examine the willingness to pay for weather insurance among rural Ethiopian households and find that farmers who behaved in a less risk-averse manner were found to be more likely to purchase insurance. In these studies, the inverse association between risk aversion and insurance take-up are explained as the consequence of the imperfect market. In order to better model farmers' risk management decisions especially in a possibly imperfect market, in this study, we use prospect theory to explain this puzzle. In a similar vein to Babcock (2015), we assume that farmers are likely to choose narrow frame and view the value of crop insurance independent from the risk of crop shortfall. It the assumption holds true, the association between risk parameters and the value of crop insurance is altered. Expected utility predicts that a risk averse and loss averse individual are more eager to seek risk protection and therefore willing to a pay higher price to purchase insurance than a risk neutral and loss neutral individual. In stark contrast, a risk averse and loss averse farmer is likely to pay less price for insurance if she is a narrow framer.

The testable hypotheses of narrow framing are 1) the risk aversion is negatively associated with the value of insurance; 2) the loss aversion is negatively associated with the value of insurance; 3) farmers are likely to choose low coverage than high coverage, even if the high coverage enable them to obtain high subsidy benefits. Intuitively, if farmers evaluate crop insurance based on the crop revenue and related risk, the premium paid is seen as a small cost taken from underwritten revenue. Under the law of diminishing marginal utility, farmers are insensitive to the cost of premium. Moreover, risk averse and loss averse farmers are likely to purchase higher coverage insurance in order to pursuit high level of risk protection. However, if farmers view the insurance as an independent lottery, a loss is felt when paying premium without any indemnity received, and the loss looms larger than the gain (the indemnity) due to loss aversion. Moreover, the narrow framing and loss aversion contribute to explain status quo bias (Kahneman et al. 1991). Because the reference point is usually the status quo, the properties of alternative options are evaluated as value of gains or losses relative to the current situation, and the value of losses is amplified by the loss aversion coefficient.

This study discusses the application of narrow framing prospect theory to explain farmers' decisions on crop insurance in an emerging market. It is proposed to provide an alternative model to explain farmers' decisions under a certain condition, where information barriers, lack of trust in and understanding of insurance program and poor quality of the insurance services are prevalent in the market. With these imperfections largely mitigated, it is likely that farmers' decision patterns would be in line with the conventional theories.

3.3 MODEL

This section explores the implications of prospect theory on crop insurance demand. Specifically, we discuss risk preference and narrow framing in more detail, examining the evidence they are inferred from and the interpretations they are given.

We analyze a farmer's decision under prospect theory framework. Let x represent the outcomes of a prospect, R represent farmer's reference point, $1-\sigma$ represent the curvature of the value function and thus σ is the coefficient of relative risk aversion (CRRA), λ represent the coefficient of loss aversion and α represent the probability weighting. The value function $v(x)$ is specified as follows:

$$v(x) = \begin{cases} (x-R)^{1-\sigma}, x > R \\ 0, x = R \\ -\lambda(R-x)^{1-\sigma}, x < R \end{cases}$$

There are several approaches to define the subjective probability, and here we follow the commonly used one defined by Prelec (1998). The corresponding subjective probability that an individual perceives is $\omega(p)$ (see Figure 3.2):

$$\omega(p) = exp\,\{-(-\,log(p))^{\alpha}\}$$

An individual faces a risky prospect that has N discrete outcomes, x_i, each with an associated probability, p_i, and she makes the decision to maximize her prospect function as follows:

$$EU = \sum_{i=1}^{N} \omega(p_i)v(x_i).$$

We consider individuals who are subject to a yield loss of L with probability p. In the context of multi-peril crop insurance (MPCI), the indemnity is paid based on farm's loss assessed right after the disaster. For convenience sake, we assume an actuarially fair

MPCI insurance pays the indemnity ($indemnity \leq L$) with probability of disaster p but pays nothing otherwise.

$$Indemnity = \begin{cases} 0, \text{if } 1-p \\ Indemnity, \text{if } p \end{cases}$$

The actuarially fair premium (AFP) is

$$\pi^f = Indemnity * p$$

One of the key elements of our model is narrow framing. Under narrow framing assumption, let's consider C denotes the insurance coverage (indemnity) purchased. The crop insurance is evaluated as value of gains or losses in separate from other risk (say L). A farmer picks coverage C to maximize her prospect function as follows:

$$EU_{NF}(C; p, \sigma, \lambda, \alpha) = \omega(p) * \big(C * (1-p)\big)^{1-\sigma} - \lambda * \big(1 - \omega(p)\big) * (C * p)^{\,1-\sigma}$$

where $EU_{NF}(\cdot)$ represents prospect utility under narrow framing, C represents coverage level or maximum indemnity.

Since the farmer evaluates insurance in isolation, she will purchase insurance if her utility from insurance is positive. Therefore, the farmer's decision can be described as:

$$\begin{cases} EU_{NF}(C; p, \alpha, \lambda, \gamma) > 0, \text{Buy insurance} \\ EU_{NF}(C; p, \alpha, \lambda, \gamma) = 0, \text{Indifferent} \\ EU_{NF}(C; p, \alpha, \lambda, \gamma) < 0, \text{Not buy insurance} \end{cases}$$

By transforming $EU_{NF}(\cdot)$ as follows, we have:

$$EU_{NF}(\cdot) = C^{1-\sigma} * (\omega(p) * (1-p)^{1-\sigma} - \lambda * \big(1-\omega(p)\big) * p^{1-\sigma})$$

$$= C^{1-\sigma} * \big(1-\omega(p)\big) * p^{1-\sigma} * \{\frac{\omega(p)}{1-\omega(p)} * (\frac{1-p}{p})^{1-\sigma} - \lambda\}$$

The prospect function $U_{NF}(\cdot)$ monotonically decreases with loss aversion, with other things are equal. Moreover, zero coverage maximizes the farmer's prospect if $\lambda \geq \frac{\omega(p)}{1-\omega(p)} * (\frac{1-p}{p})^{1-\sigma}$, that is, if λ is large enough, farmers are expedited not to buy any insurance. In addition, if we expect the probability of disaster is less than 0.5, then $\frac{1-p}{p}$ is greater than 1. Thus, $(\frac{1-p}{p})^{1-\sigma}$ is increasing with $1-\sigma$ and therefore decreasing with σ. The prospect function is a decreasing function with σ.

The celebrated theorem of Mossin (1968) states that individuals who maximize expected utility will buy full insurance in face of AFP. By contrast, when farmers frame the insurance narrowly, they are less likely to purchase insurance than with expected utility, even when the policies are actuarially fair. Therefore, farmers would choose zero coverage if they are sufficiently risk averse or loss averse. Importantly, since farmers in our model view insurance as a risky investment, and thus a more risk loving individual is more likely to purchase insurance and vice versa. This prediction is consistent with the findings in previous studies (Giné et al., 2008; Cole et al., 2013; Hill et al., 2013) and our results in China.

Proposition I: If farmers are narrow framers, the prospect function from purchasing an insurance policy is a decreasing function of risk aversion (σ) *and loss aversion* (λ). *Therefore, farmers' risk aversion and loss aversion are negatively related to the value of insurance.*

For the model suggests farmers consider the wealth level when they engage in full coverage insurance as reference point as reference point, the value function can be seen as a constant $W-L*p$ under all states. Under such framing assumption, consider a farmer picks coverage C of an alternative insurance contract. Recall that $C \leq L$, thus her value function is

$$v(x)=\begin{cases} \left(W-C*p-(W-L*p)\right)^{1-\sigma}=\left((L-C)*p\right)^{1-\sigma}, if\ 1-p \\ -\lambda*\left(W-L*p-(W-L+C-C*p)\right)^{1-\sigma}=-\lambda*\left((L-C)*(1-p)\right)^{1-\sigma}, if\ p \end{cases}$$

where W denotes the wealth or crop revenue. The farmer maximizes her prospect function as follows:

$$EU_{Alt}(\cdot) = \left(1 - \omega(p)\right) * \left((L - C) * p\right)^{1-\sigma} - \lambda * \ \omega(p) * \left((L - C) * (1 - p)\right)^{1-\sigma}$$

Hence, if other things are equal, the higher λ, the more loss the farmer feels due to insufficient risk protection, and the more likely she chooses to buy full coverage insurance (stay the original status). Moreover, $EU_{Alt}(\cdot)$ is an increasing function of risk aversion (σ). Therefore, farmers' risk aversion and loss aversion are positively related to the value of insurance.

Proposition II: If farmers consider the wealth level when they engage in full coverage insurance as reference point (broader frame), the prospect function from purchasing an insurance policy is a decreasing function of risk aversion (σ) *and loss aversion* (λ)*. Therefore, farmers' risk aversion and loss aversion are positively related to the value of insurance.*

3.4 FIELD EXPERIMENT AND DATA

To test our hypothesis, we run a survey including three experiments to assess farmers' demand for crop insurance and their risk preference. The survey was conducted in Shunyi, a northern suburb of Beijing China. 477 vegetable farmers were selected at random from 13 villages.

To measure farmers' risk parameters, we replicated the procedure that Tanaka et al. (2010) (TCN) developed to elicit individual's risk parameters-risk aversion, loss aversion and probability weighting. To measure farmers' insurance demand, we designed two experiments. One experiment is based on a set of hypothesized insurance contracts. We provide farmers three insurance contracts with coverage 30%, 60%, 90%. Farmers were asked willingness-to-pay under each coverage level respectively. The other experiment focuses on a real insurance contract available in the market. When the survey took place, MPCI was available for vegetable growers in Beijing suburban areas. The government subsidizes 80% of the premium, and eligible growers only pay 20% of the premium. However, due to issues such as lack of financial literacy or poor propaganda, the information of this insurance is not equally available for all the farmers in our sample. We asked farmers' willingness to purchase the MPCI insurance contract under different coverage level. The detailed description of the experiments is as follows.

3.4.1 Risk Preference Experiment

To measure participants' risk preference, we run TCN experiment to elicit the measure of risk aversion (σ), loss aversion (λ) and probability weighting (α). The design of this experiment followed standard TCN procedures.

In the game, we presented farmers three tables (see Appendix II Table 4-6) with a set of pair-wise lotteries in each. The participants decided whether they preferred Lottery A or Lottery B. The enumerators verbally explained the table, pointing out that Lottery A had an unvarying payoff and Lottery B had an increasing payoff down to the list, and that participants were allowed to switch only once at most. We also explained that a random line on the table would be chosen ex-post and the lottery they preferred at that line would be played for actual the game's stake. A trial with exactly the same procedures, but no payoff, was played to help the participants become familiar with the decision-making process. In the trial, the participants chose a lottery they preferred for each line for each series. Once the switching point or never switching was determined, the enumerator asked participants' their choices for upper and lower options to confirm the answers were consistent. Once the participant felt comfortable she continued with the formal game, the lottery with money payment was played.

A unique combination of CPT parameters (σ, α) can be calculated from each participant's choices in series 1 and 2. The expected utilities of prospect of two lotteries are set to equal at each row. This yields $12 \times 14 = 168$ combinations of (σ, α). Based on the estimate of (σ, α), we calculated λ from series 3.

$$exp\{-(-ln(0.3))^{\alpha}\} * (15)^{1-\sigma} + (1 - exp\{-(-ln(0.3))^{\alpha}\}) * (5)^{1-\sigma}$$
$$= exp\{-(-ln(0.1))^{\alpha}\} * (x_1)^{1-\sigma}$$
$$+ (1 - exp\{-(-ln(0.1))^{\alpha}\}) * (2)^{1-\sigma}$$
$$exp\{-(-ln(0.1))^{\alpha}\} * (20)^{1-\sigma} + (1 - exp\{-(-ln(0.9))^{\alpha}\} * (15)^{1-\sigma})$$
$$= (1 - exp\{-(-ln(0.3))^{\alpha}\}) * (x_2)^{1-\sigma}$$
$$+ exp\{-(-ln(0.3))^{\alpha}\} * (2)^{1-\sigma}$$
$$x_3^{1-\sigma} + \lambda * x_4^{1-\sigma} = 18^{1-\sigma} + \lambda * x_4^{1-\sigma}$$

There were 1008 combinations of $(\alpha, \gamma, \lambda)$ in total. The individual's estimates of the three parameters were defined as the midpoint between the switched row and the row above. A switch at the first row was defined as the estimate of switch at the first row, and never switch the estimate of switch at the last row.

The mean values for the risk aversion, loss aversion, and probability parameter weighting parameters $(\sigma, \alpha, \lambda)$ are (0.27, 0.83, 2.30), indicating that on average farmers are risk averse, loss averse and have a tendency to overweight low probabilities. Similar to the result of TCN (Tanaka et al., 2010) found (0.40, 0.74, 2.59) for their samples in

Vietnam and Tversky and Kahneman (1992) estimated (0.12, 0.61(0.69), 2.25)[5]. Farmers in the study show mild risk aversion (σ is slightly greater than 0), and they seem hold a quite neutral perceived probability of disasters (α is close to 1), while the loss aversion is similar to previous estimation.

3.4.2 WTP Experiment

This experiment was aimed to elicit farmers' WTP for hypothesized insurance contracts with three coverage levels, 30%, 60% and 90%. Farmers were presented three tables, one for each coverage level, showing two hypothesized 20-year series of revenue per unit of area in yuan without and with insurance (See Appendix II Table 1-3). The revenue series with insurance does not account for the insurance premium. Therefore, the insured series is first stochastic dominant to the uninsured series. We asked participants that if they had the uninsured revenue, what the maximum price that they were willing to pay to switch from the uninsured revenue series to the insured one. Rather than asking an open-end question, we provided 12 price options.

In order to make farmers focus on the features of the revenue series we provided instead of on their own farming experience, we chose okra, which is rarely grown in that area, as the underwritten crop being portrayed the game. We assumed that farmers' revenues from growing okra follow a normal distribution with a mean of 15000 and a standard deviation of 5000 yuan. The 20-year revenue streams were drawn from the distribution. The insured revenue in year i was computed as follows:

$$rev_{i,c}^{ins} = max(rev_i, c * \overline{rev}),\, i = 1,2,\cdots,20$$

[5] In (Tanaka et al., 2010) and Tversky and Kahneman (1992), the estimate of curvature of value function, which is comparable to σ in this paper. Tversky and Kahneman (1992) estimated two probabilities weighting for positive and negative outcome respectively.

Where rev_i represents uninsured revenues in year i (in the right column); c is the coverage level and c= 30%, 60% and 90%; $\overline{rev}$ stands for the sample mean of the uninsured revenues. The 12 price options were varied across coverage levels, taking on values from 0% to 180% of the AFP in 20% increments. The AFP is calculated as follows:

$$\pi_c^f = \frac{1}{20}\sum_{i=1}^{20}(rev_{i,c}^{ins} - rev_i)$$

Table 3 shows an example of the tables (the coverage level=30%). The AFP of this contract is 147 yuan. The option B is 20% of the AFP and Option J is 180% of the AFP.

Regarding the experimental protocol, farmers were presented the table and then enumerators verbally described the key features of the revenue series to the farmers such as the values of the mean, the extreme values, the frequency of a covered revenue loss, and the maximum indemnity provided by the insurance contract. The participants were also told that in order to secure the better (insured) revenue series, they had to offer a price that was higher than the one we kept in secret, which was the fair value of the insurance. After the decisions were made, farmers were told whether or not they got the insurance revenue series. If they didn't, a number i from 1 to 20 was drawn and 0.001 of the uninsured revenue at year i was paid to them. If they did, they received 0.001 of the insured revenue at year i minus the price they offered.

A trial was played before the formal experiment to familiarize the farmers with the experimental protocol. The trial included three rounds for each coverage level. All the procedures were the same as in the formal game but the revenue series were different and no payment was won. At the end of the formal experiment, we used a random incentive device to determine which of the three rounds the payment would be based on, in order to encourage the participants to be mindful of their decisions at all three coverage levels.

Farmers' answers were translated into the percent of the AFP at each coverage level. For instance, if a farmer chose "B" for the coverage 30%, his relative price is recorded as 0.2. Figure 4 shows farmers' choice under three coverage levels. Most farmers offered relative price lower than the AFP, showing that they have low WTPs for the hypothesis contracts. In addition, farmers in our data are willing to offer higher relative price for low coverage level than high coverage level.

3.4.3 Coverage Choice Experiment

The purpose of the third experiment was to observe farmers' choices in a real world context. Moreover, we are interested in whether the effects of risk preferences on insurance demand would be mitigated by the subsidy or still play a role under a high subsidy rate (80% of premium). Currently, vegetable insurance contract provides a single value of maximum indemnity, which is roughly equivalent to 30% of the average revenue. The government subsidizes 80% of the premium and transfers directly to the insurance company, so farmers only need to pay 20% of the premium. The low coverage ensures the low premium, which probably is affordable for the majority of the farmers. However, the risk protection offered by the insurance contract is limited. In the experiment, we presented farmers a series of hypothesized insurance options with varying indemnity values and premiums, and asked farmers' a "take it or leave it" decision at each level. The subsidy rate was fixed at 80% for all the contracts. The maximum indemnities were equivalent to coverage levels ranging from 10-90% of the average revenue. Figure 3 illustrates a part of the contracts we showed to farmers. Figure 4 reports the percentages of "buy" decisions over varying coverage levels. Even with the 80% premium subsidy, farmers' oral agreement to take up MPCI is low. Our data also reveals that farmers are likely to turn down the contracts that provide high transferring benefits and settle for low level of risk protection. The suboptimal choice is similar to the US crop insurance market documented in Du et al (2015).

3.5 REGRESSION MODEL AND RESULTS

3.5.1 Risk Parameters and Farmers' Value of Insurance

We use OLS regression to control for observed individual characteristics and get a statistical test of the risk parameters for farmers' value of insurance. In WTP experiment, we collected farmers' WTP for three coverage levels. Farmers' answers were translated into the percent of the AFP at each coverage level. For instance, if a farmer chose "B" for the coverage 30%, his outcome variable (wtp_30) is recorded as 0.2. Estimating equations are as follows:

$$wtp\_CL_i = \beta_0 + \beta_1 * \sigma_i + \beta_2 * \lambda_i + {X_i}^T \Phi + \varepsilon_i$$

where wtp_CL_i denotes the choice of farmer i for a coverage level CL (CL=30%, 60%, and 90%), X_i is a vector of observable individual characteristics. Table 3.1 presents the OLS results. The results are consistent with the predictions: 1) the higher loss averse, the lower the value of insurance; 2) the more risk averse, the lower the value of insurance. The outcome variable of columns (1)-(6) is the percent of AFP farmers offered in order to get the hypothesized insurance. Columns 1, 3 and 5 report results for a simple model that includes only risk aversion and loss aversion for each coverage level, while Columns 2,4 and 6 are the specifications where the other controls are also included. The regression results show that loss aversion (λ) significantly farmers' value of crop insurance. In contrast, results in columns (1) and (2) indicate that the risk aversion has no explanatory power in explaining farmers' value for low coverage. Although not statistically significant, risk aversion has the negative sign as expected.

In addition, by comparing all the three coverage levels (1), (3), (5), we find the coefficients of risk parameters increase with the coverage level, which suggests that the negative impact of risk parameters become greater when farmers face higher value of "investment". The results are consistent when we add other control variables (columns (2), (4), (6)). Overall, the results suggest that farmers are likely to be narrow framers rather than broader framers.

To examine if the results are consistent with the insurance take-up decisions, logistic regression are employed. We transform the outcome variables above as follows:

$$buy\_CL_i = \begin{cases} 1, if\ wtp_{CL_i} > 1 \\ 0, otherwise \end{cases}$$

The Logistic regression results in Table 6 are also consistent with the predictions. Results in columns (1)-(2) shows that while the measure of risk aversion and loss aversion are not significant at 5%, the two parameters has a significant negative association with crop insurance take-up. The results are also consistent with the trend over coverage levels: the impact of risk parameters rises with coverage level.

3.5.2 Risk Parameters and Farmers' Coverage Choice

To further test whether the impact of risk parameters is consistent, we examine how risk parameters are associated with farmers' coverage choice. If farmers' opinion toward insurance is closer to a technology rather than a risk protection instrument, a more risk tolerant and loss insensitive individual is likely to investment more, meaning, buy higher coverage insurance. By contrast, risk averse and loss averse farmers are likely to choose “not to buy” high coverage insurance in order to avoid “wasting” high premium payment if the indemnity does not happen.

Table 3.2 presents coefficient estimates when the outcome variables are the maximum coverage level farmers chose in Coverage Choice Experiment. In the Coverage Choice Experiment we asked farmers’ buy-or-not buy decisions for the coverage levels $20\%, 30\%, \cdots, 90\%$ with an 80% premium subsidy. It is important to note that the subsidy rate was 80% at each coverage, and thus, the highest coverage provides farmers the most monetary benefit in expectation. We translate farmers’ a set of choices for each coverage level into the interval a farmer is willing to accept. For example, if a farmer said yes to purchase from 20% coverage all the way up to 70% and denied 80%, her outcome variable is represented as an interval “2 to 7”. If a farmer only answered “yes” once, for insurance at 30% coverage, and rejected all the other coverage, her outcome variable is “3 to 3”. The regression is specified as follows:

$$Coverage\ interval_i = \beta_0 + \beta_1 * \sigma_i + \beta_2 * \lambda_i + {X_i}^T \Phi + \varepsilon_i$$

where $Coverage\ interval_i$ represents the coverage interval accepted by farmer i; other notations are the same. The results (see Table 3.3) show that risk aversion and loss aversion coefficients are statistically significant in farmers’ coverage choices. Risk averse and loss averse farmers prefer low coverage contract even low coverage contracts provide them less subsidy benefits.

3.6 CONCLUSION

In the data we collected in this paper, combining with findings in previous studies (Giné et al., 2008; Cole et al., 2013; Hill et al., 2013), discover a consistent counterintuitive phenomena: risk averse farmers are less likely to purchase crop insurance. The paper tests whether prospect theory is able to explain this unsolved puzzle. The novel feature of the prospect theory model is that it assumes individuals are narrow framers and loss averse. Under such assumption, farmers are likely to view crop insurance in separate from the crop shortfall risk. Therefore, paying premium is seen as certain loss and receiving indemnity as a lucky event. If loss aversion is large enough, an actuarially fair or even favorable insurance can be rejected. Similarly, if a farmer is quite risk averse, she is likely to reject an insurance contract to get avoid of having additional risk.

The results shows that prospect theory model provides a better model framework to predict farmers' insurance choices than rational model in an imperfect market, where information barriers are prevalent and the implement of the insurance contracts is heavily doubted. In developing countries, farmers may have limited experience and knowledge on purchasing insurance. Once an innovative insurance service brings to market, it is often that farmers focus on the insurance contract’s own value and neglect its risk transferring benefits. Lack of trust, understanding and credit constraint that are discussed in previous studies may also play a role in farmers’ decision as a small transition costs. As a result, farmers are likely to stick with status quo and do not take any action even in face of favorable premiums. In the study area, crop insurance program has been subsidized by government for seven years. However, the take-up rate does not live up to the expectation. Our data also discloses that farmers are more willing to accept low coverage contracts than high coverage contracts. A possible explanation is that a small stake (low coverage contract) seems more attractive to narrow framing farmers than a large one.

In order to boost the take-up of crop insurance, government usually provides high subsidy to insurance program. Although subsidy interventions have helped to increase the participation rate, unfortunately, our data shows that high premium subsidy has limited effect to mitigate the narrow framing choices. Farmers who hold conservative opinions toward risk might not reap the benefits of the subsidy transferring. As the findings in many studies suggested, farmers who are too risk averse and loss averse could not as quickly embrace technological innovations as risk tolerant and loss insensitive farmers (Tanaka et al., 2010; Liu, 2013). The inequality in distributing premium subsidy will be persistent over time if narrow framing choices are not corrected. The findings of this study shed light on the effectiveness of premium subsidy policy in the development of the crop insurance market. Other interventions, such as can be considered to improve farmers' understanding of insurance and build trust between insurance company and farmers.

Table 3.1 OLS Regression of Farmers' Value of Insurance under Three Coverage Levels

	(1) 30%	(2) 30%	(3) 60%	(4) 60%	(5) 90%	(6) 90%
Risk aversion	-0.080	-0.043	-0.135**	-0.112*	-0.119*	-0.104*
(σ)	(0.065)	(0.066)	(0.068)	(0.068)	(0.064)	(0.061)
Loss aversion	-0.022*	-0.021**	-0.026*	-0.025*	-0.032**	-0.031***
(λ)	(0.011)	(0.010)	(0.015)	(0.014)	(0.013)	(0.012)
Probability		0.132***		0.093*		0.058
weighting (α)		(0.047)		(0.057)		(0.063)
Gender		0.064		0.122**		0.087
(female=1)		(0.046)		(0.062)		(0.062)
Age		-0.009**		-0.002		-0.003
		(0.004)		(0.005)		(0.004)
Years of		0.005		0.013		0.008
education		(0.010)		(0.010)		(0.012)
Size of land		0.001		0.002		0.001
		(0.002)		(0.002)		(0.002)
Constant	1.103***	1.354***	0.913***	0.709*	0.863***	0.854**
	(0.063)	(0.287)	(0.080)	(0.363)	(0.085)	(0.353)
Observations	477	477	477	477	477	477
R^2	0.009	0.038	0.015	0.039	0.021	0.035

Bootstrapped standard errors are clustered at the village level. The dependent variables are farmers' choices under each coverage level. It takes the values of 0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6 or1.8. Risk aversion (CRRA) takes value (-1, 1). We allow farmers to be risk loving in the design of TCN game. A farmer whose risk aversion less than 0 means she is risk loving. Loss aversion (λ) takes value from 0 to 14. We also allow farmers to be loss insensitive in the design of TCN game. A farmer whose risk aversion less than 1 indicates she is insensitive to loss than gain. Probability weighting (α) takes the values (0, 2). An individual tend to overvalue the probability of small event if α<1. Years of education takes the values of 3, 6, 9, 12 or 18.

Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2 Interval Regression of Farmers' Coverage Choice

	(1)	(2)
Risk aversion (σ)	-0.091***	-0.077**
	(0.034)	(0.034)
Loss aversion (λ)	-0.374***	-0.370***
	(0.121)	(0.132)
Probability weighting (α)		-0.049
		(0.271)
Gender (female=1)		0.072
		(0.214)
Age		-0.035*
		(0.018)
Years of education		0.065
		(0.043)
Size of land		-0.009
		(0.006)
Constant	2.737***	4.370***
	(0.244)	(1.209)
Ln(sigma) Constant	0.476***	0.454***
	(0.138)	(0.133)
Observations	477	477

Bootstrapped standard errors are clustered at the village level. The dependent variables are the coverage interval farmers accept to purchase. It takes the values of 0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6 or1.8. Risk aversion (CRRA) takes value (-1, 1). We allow farmers to be risk loving in the design of TCN game. A farmer whose risk aversion less than 0 means she is risk loving. Loss aversion (λ) takes value from 0 to 14. We also allow farmers to be loss insensitive in the design of TCN game. A farmer whose risk aversion less than 1 indicates she is insensitive to loss than gain. Probability weighting (α) takes the values (0, 2). An individual tend to overvalue the probability of small event if α<1. Years of education takes the values of 3, 6, 9, 12 or 18.

Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$

Table 3.3 Logistic Regression of Farmers' Take-up of Insurance under Each Coverage Level

	(1) 30%	(2) 30%	(3) 60%	(4) 60%	(5) 90%	(6) 90%
Risk aversion	-0.397	-0.324	-0.602**	-0.491*	-0.567**	-0.497**
	(0.297)	(0.308)	(0.281)	(0.282)	(0.267)	(0.239)
Loss aversion	-0.089*	-0.087	-0.167*	-0.169*	-0.217*	-0.214*
	(0.054)	(0.055)	(0.092)	(0.095)	(0.112)	(0.111)
Probability		0.285		0.489*		0.333
weighting		(0.280)		(0.260)		(0.364)
Gender		0.229		0.433		0.491*
(female=1)		(0.198)		(0.264)		(0.287)
Age		-0.027		-0.017		0.007
		(0.018)		(0.021)		(0.020)
Years of		0.020		-0.008		0.041
education		(0.049)		(0.054)		(0.063)
Size of land		0.005		0.007		0.007
		(0.005)		(0.006)		(0.012)
Constant	-0.536**	0.224	-0.803**	-0.724	-0.836*	-2.434
	(0.228)	(1.387)	(0.347)	(1.671)	(0.436)	(1.707)
Observations	477	477	477	477	477	477

Bootstrapped standard errors are clustered at the village level. The dependent variables are indicator variables if a farmers' choice is higher than 1 in WTP Experiment. Risk aversion (CRRA) takes value (-1, 1). We allow farmers to be risk loving in the design of TCN game. A farmer with $\sigma < 0$ means she is risk loving. Loss aversion (λ) takes value from 0 to 14. We also allow farmers to be loss insensitive in the design of TCN game. A farmer with $\lambda < 1$ indicates she is insensitive to loss than gain. Probability weighting (α) takes the values (0, 2). An individual tend to overvalue the probability of small event if α<1. Years of education takes the values of 3, 6, 9, 12 or 18.
Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

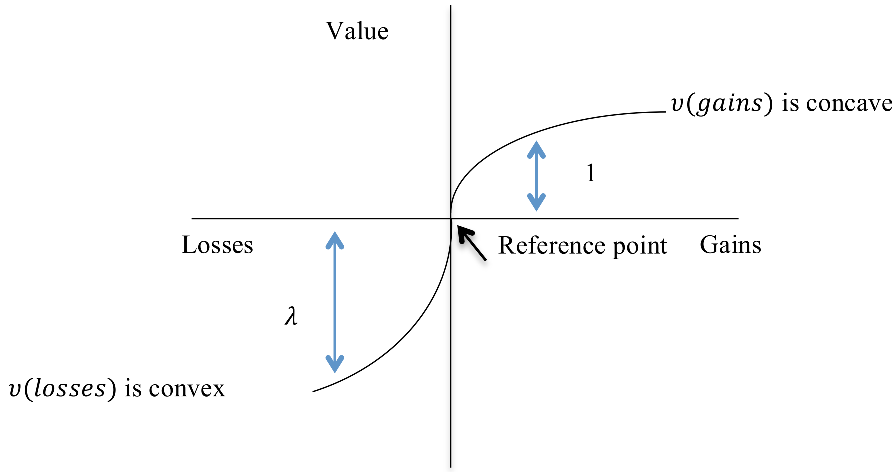

Figure 3.1 The Three Parameters of Risk Preference: Reference Point, Loss Aversion and Risk Aversion

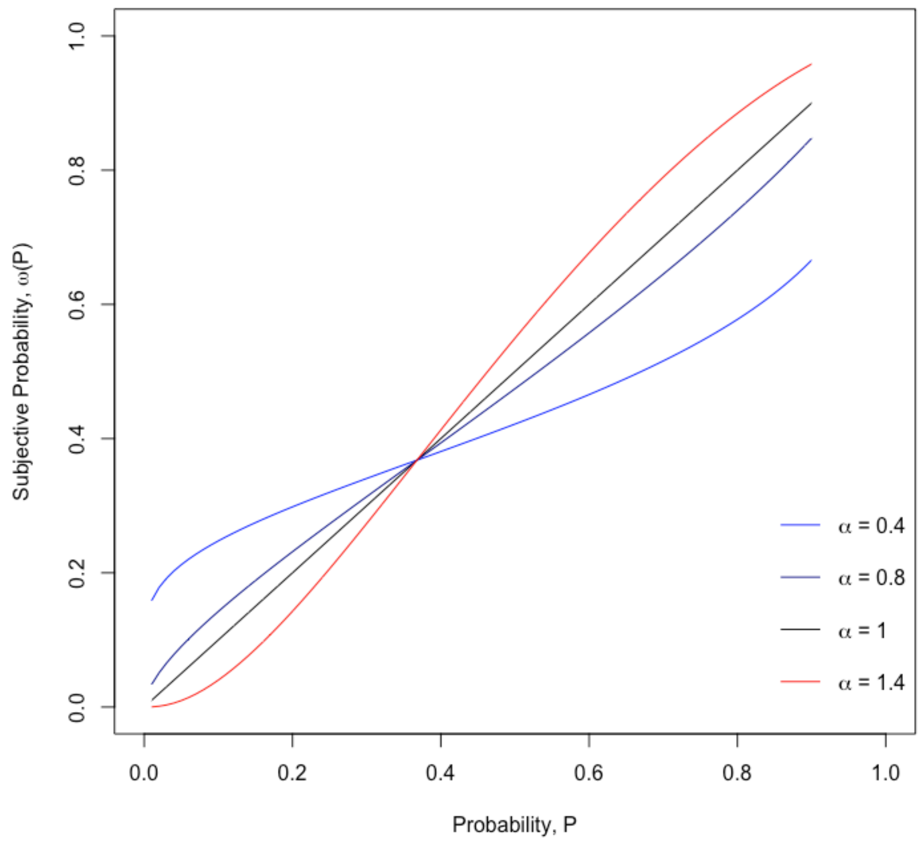

Figure 3.2 The Prelec Probability Weighting Function

BIBLIOGRAPHY

Babcock, B.A., 2015. Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice. *American Journal of Agricultural Economics,* 97(5), pp.1371-1384.

Barberis, N., Huang, M. and Thaler, R.H., 2006. Individual Preferences, Monetary Gambles, and Stock Market Participation: A Case for Narrow Framing. *American Economic Review,* 96(4), pp.1069-1090.

Barberis, N.C., 2013. Thirty Years oProspect Theory in Economics: a Review and Assessment. *Journal of Economic Perspectives,* 27(1), pp.173-96.

Boucher, S. and Mullally, C., 2010. Evaluating The Impact of Index Insurance on Cotton Farmers in Peru. *Technical Notes* IDB TN, 198.

Cai, J. and Song, C., 2017. Do Disaster Experience and Knowledge Affect Insurance Take-up Decisions? *Journal of Development Economics,* 124, pp.83-94.

Clarke, D., 2010. A theory of Rational Hedging. *Mimeo, University of Oxford,* Oxford, UK.

Cohen, A. and Einav, L., 2007. Estimating Risk Preferences from Deductible Choice. *American Economic Review*, 97(3), pp.745-788.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J., 2013. Barriers to Household Risk Management: Evidence from India. American *Economic Journal: Applied Economics*, 5(1), pp.104-35.

Dercon, S., Hill, R.V., Clarke, D., Outes-Leon, I. and Taffesse, A.S., 2014. Offering Rainfall Insurance to Informal Insurance Groups: Evidence from a Field Experiment in Ethiopia. *Journal of Development Economics*, 106, pp.132-143.

Du, X., Feng, H. and Hennessy, D.A., 2016. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics,* 99(3), pp.732-756.

Elabed, G. and Carter, M.R., 2015. Compound-Risk Aversion, Ambiguity and the Willingness to Pay for Microinsurance. *Journal of Economic Behavior & Organization,* 118, pp.150-166.

Galarza, F., 2009. Choices under risk in rural Peru. *University of Wisconsin-Madisson.*

Gaurav, S., Cole, S. and Tobacman, J., 2011. Marketing Complex Financial Products in Emerging Markets: Evidence from Rainfall Insurance in India. *Journal of Marketing Research,* 48(SPL), pp.S150-S162.

Giné, X. and Yang, D., 2009. Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi. *Journal of development Economics,* 89(1), pp.1-11.

Giné, X., Townsend, R. and Vickery, J., 2008. Patterns of Rainfall Insurance Participation in Rural India. *The World Bank Economic Review*, 22(3), pp.539-566.

Harrison, G.W., Humphrey, S.J. and Verschoor, A., 2009. Choice under Uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal,* 120(543), pp.80-104.

Hazell, P.B., 1992. The Appropriate Role of Agricultural Insurance in Developing Countries. *Journal of International Development,* 4(6), pp.567-581.

Hill, R.V., Hoddinott, J. and Kumar, N., 2013. Adoption of Weathe Index Insurance: Learning from Willingness to Pay among a Panel of Households in Rural Ethiopia. *Agricultural Economics,* 44(4-5), pp.385-398.

Kahneman, D. and Lovallo, D., 1993. Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk Taking. *Management Science,* 39(1), pp.17-31.

Kahneman, D. and Tversky, A., 2013. Prospect Theory: an Analysis of Decision under Risk. *In Handbook of the Fundamentals of Financial Decision Making*: Part I (pp. 99-127).

Kahneman, D., Knetsch, J.L. and Thaler, R.H., 1991. Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives,* 5(1), pp.193-206.

Kahneman, D., 2003. Maps of Bounded Rationality: Psychology for Behavioral Economics. *American Economic Review*, 93(5), pp.1449-1475.

Liu, E.M., 2013. Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *Review of Economics and Statistics,* 95(4), pp.1386-1403.

Mahul, O. and Stutley, C.J., 2010. Government Support to Agricultural Insurance: Challenges and Options for Developing Countries. *The World Bank.*

Miranda, M.J. and Farrin, K., 2012. Index Insurance for Developing Countries. *Applied Economic Perspectives and Policy*, 34(3), pp.391-427.

Mossin, J., 1968. Aspects of Rational Insurance Purchasing. *Journal of Political Economy,* 76(4, Part 1), pp.553-568.

Petraud, J., Boucher, S. and Carter, M., 2015. *Competing Theories of Risk Preferences and the Demand for Crop Insurance: Experimental Evidence from Peru* (No. 1008-2016-80041).

Prelec, D., 1998. The Probability Weighting Function. *Econometrica,* 66(3), pp.497-528.

Read, D., Loewenstein, G., Rabin, M., Keren, G. and Laibson, D., 1999. Choice Bracketing. *In Elicitation of preferences* (pp. 171-202). Springer, Dordrecht.

Sydnor, J., 2010. (Over)insuring Modest Risks. American Economic Journal: *Applied Economics,* 2(4), pp.177-99.

Tanaka, T., Camerer, C.F. and Nguyen, Q., 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review,* 100(1), pp.557-71.

Tversky, A. and Kahneman, D., 1981. The Framing of Decisions and the Psychology of Choice. *Science*, 211(4481), pp.453-458.

Tversky, A. and Kahneman, D., 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, 5(4), pp.297-323.

CHAPTER 4

A PROBABILISTIC MODEL OF INDIVIDUAL CROP INSURANCE PURCHASE DECISION

Abstract

This chapter focuses on the challenge for farmers to evaluate crop insurance policies and estimate the actuarially fair premium (AFP) underlying a policy. Recognizing this challenge, we develop a probabilistic model incorporating individual's biased estimates of the AFP in order to explain economically suboptimal take-up of crop insurance by smallholder farmers. Evidence from the probabilistic model employing data from the economic surveys and experiments partially explains the anomalous decisions found in the first essay. Critically, we find that farmer risk aversion, average propensity to consume, and other key sociodemographic variables have explanatory power for farmers' willingness to pay for a crop insurance contract and farmers' estimate of the AFP for a crop insurance contract.

4.1 INTRODUCTION

The provision of accessible risk protection tool to smallholder farmers plays an important role in the economic growth of developing countries (Morduch, 1995). In practice, the take-up of crop insurance is unexpectedly low, despite its importance in shielding farmers from crop shortfall risks and favorable prices subsidized by government sectors. The puzzle of low take-up has been investigated in a large body of literature. In most previous studies on farmers' demand for crop insurance, there is an implicit or explicit assumption that farmers know the actuarially fair premium with certainly. However, there is no statutory requirement that the premium set at the individual level be such. In this study, we relax the assumption and consider a probabilistic model, which explicitly recognizes that farmers are uncertain about the exact value of the actuarially fair premium (AFP) underlying the desired policy. Our model suggests that, due to this uncertainty about their AFP, some rational individuals might not purchase insurance even if they are risk-averse and their premiums are highly subsidized. Once the possibility that crop insurance premiums may be biased for some farmers is incorporated, then certain anomalies surrounding farmers' crop insurance choices may be partly explained.

At aggregate levels, AFPs are supposed to reflect expected indemnities of the insured. It does not necessarily hold at an individual level. Farmers make a decision whether to purchase crop insurance contract or the amount of insurance based on their perceptive of yield risk. Subsidies make crop insurance more attractive for farmers by transferring part of the premium cost to the public. Numerous studies have been conducted to analyze heterogeneous choices of individuals to participate in crop insurance programs. Miranda (1991) points out that an individual farmer's total yield risk can be decomposed into a systemic component and an idiosyncratic component, and producers who recognize that their expected yield risk exceed their premiums are likely to purchase insurance. Just et al. (1999) considered data from a 1989 survey and concluded that risk-aversion is a relatively weak incentive for participation. Instead, they suggested that farmers' asymmetric informational advantages and subsidy benefits lead to incentives to purchase crop insurance. Their analysis assumed that yield risk was the only source of uncertainty faced by the farmer and that the actuarially fair premium was treated as fixed and known by the producer. Sherrick et al. (2004) utilizes a mail survey of Midwestern U.S. farmers and identify the influences of individuals' yield risk and other demographic variables on the crop choices of insurance products. Ramirez et al. (2015) used elaborate Monte Carlo simulations and provides sight into whether the federal crop insurance subsidies are equitably distributed across producers. Farmers' choices on crop insurance in developing markets, even more, depart from the predictions of the rational theory. Trust issues, familiarity with the insurance product, connection to the social network, or credit constraints play a significant role in farmers' participation decisions. Giné et al. (2008) used household survey data to explore farmers' demand for rainfall index insurance. They disclosed a set of factors, including credit constraints, basis risk, risk aversion, trust and so forth, which are closely related to farmers' insurance take-up decisions. They found the impacts of some factors are not consistent with the predictions of a rational mode. Their results reflect the patterns of household demand for crop insurance are uncertain about given their limited insurance experience. Cole et al. (2012) used a series of randomized field experiments in rural India and presented evidence that the demand of smallholder farmers for rainfall index insurance are very price sensitive. Cai and Song (2013) and Lybbert et al. (2010) conducted field experiments on insurance take-up in rural areas in different developing courtiers. The common findings of the two studies suggested that providing knowledge on insurance significantly helps to boost insurance take-up. Karlan et al. (2013) examined the impact of networks on insurance take-up. Cole (2013) examined a seven-year panel data of rainfall insurance purchase decisions made by rural farming households in India. Their findings suggested the experience in insurance payouts, especially multiple time payouts increase famers' take-up. In summary, individual demand for crop insurance is driven by multiple factors. In the US crop insurance market, where farmers have rich experience in purchasing insurance, the patterns of their demand are more in line with rational theory than their peers in developing world, and crop yield is considered as the main source of variation in individual insurance choices. In the developing world, farmers' choices are hard to predict. Price sensitivity of insurance demand suggests that farmers' choices may not be closely based on the actuarial value. In addition, due to various frictions, farmers' insurance take-up is considerably suboptimal and involves more uncertainty.

In order to model the suboptimal demand for crop insurance, we formulate a tractable framework in the form of a mathematical statistics framework on individuals' willingness to pay for a crop insurance contract that explicitly recognizes that not all the farmers know the exact value of the AFP underlying the desired policy. Incorporating the uncertain feature of farmers' insurance demand, this model measures the bias and errors of farmers' estimated AFP. More importantly, we use the model to identify the farmers' characteristics variables that affect the level of bias and random error in their premium estimates. Last, our model can be used to help insurers or government alike to anticipate the probability of participation in a target area given a certain subsidy level.

Our study contributes to a large literature studying the household insurance market participation in developing countries. Unlike the previous work to explore the reasons for low take-up or test some specific barriers, our study focus on exploring a mathematical framework to model farmers' demand with uncertainty. The analyses also shed light on some of the factors driving the current performance of the US crop insurance program.

4.2 CONCEPTUAL FRAMEWORK

Standard rational utility theory suggests that a farmer's decision to purchase crop insurance is shown in Figure 4.1. Farmer i's willingness to pay (WTP_i) for a crop insurance contract is the sum of AFP of the crop insurance designed for a given area and her risk premium (RP_i).

$$WTP_i = AFP + RP_i$$

Specifically, if the insurance is priced at AFP, farmer i's probability of take-up is:

$$P_i = \begin{cases} 1, if\ RP_i > 0 \\ 0, if\ RP_i \leq 0 \end{cases}$$

where Pi is the probability that farmer i will purchase insurance and RP_i is the monetary risk premium that she is willing to pay for the insurance contract apart from AFP. Note that risk premium (RP) is positive for risk-averse and negative for risk-loving individuals. The magnitude of the risk premium is determined by the farmer's level of risk aversion, the functional form assumed for her utility function, and the expected value of the contract. The expressions in equation implicitly assume that farmers know the actuarially fair premium of the insurance contract and that they are offered the contract at that AFP.

In practice, however, it is highly unlikely that the farmers actually know what the exact AFP of the contract is. Statistically, this can be represented as follows:

$$AFPE_i = AFP + \varepsilon_i$$

where $AFPE_i$ is what the farmer thinks the actuarially fair value of the insurance contract is, and ε_i is errors in AFP "estimation" by the farmer. The price of insurance contract is set as AFP. s is the percentage of the premium estimate that is subsidized by the government. Under these conditions, the probability of participation becomes:

$$P_i = Pr[\, AFPE_i + RP_i > (1-s)\, AFP \,] = Pr[\, WTP_i > (1-s)\, AFP \,]$$

where $WTP_i = AFPE_i + RP_i$ is the maximum amount that farmer i is willing to pay for the insurance contract. Note that WTP_i on the other hand, is driven by the farmer's perception to assess the fair value of the contract as well as her attitudes towards risk. Empirically, it is possible to independently elicit lower and upper bounds for WTP_i and the risk aversion coefficient (ρ_i) through separate experiments. Bounds for $AFPE_i$ and RP_i and cannot be directly elicited but, as detailed later, can be indirectly inferred on the basis of the WTP_i and ρ_i bounds. In the next two sections, we describe the experiments used to obtain those bounds.

4.3 THE EXPERIMENTS

We designed two experiments to elicit the farmers' willingness to pay for a stylized insurance product and their risk aversion levels respectively. The payoffs of two experiments were independent of each other. The overall expected payoff was approximately 50 yuan, which is equivalent to half day's wage in that area. The maximum possible payment was 537 yuan. Since we did not pay a show-up fee, we compensated up to 15 yuan to the participants whose payoff was less than this amount. However, we did not tell them of the minimum payment ex ante and there were only 4 farmers who got a combined payoff less than 15 yuan in the experiments.

4.3.1 Willingness to Pay Experiment

This experiment was designed to elicit the farmers' willingness to pay for crop insurance under three coverage levels, 30%, 60% and 90%. Farmers were presented three tables, one for each coverage level, showing a stylized 20-year series of revenue per unit of area in yuan without and with insurance (See Appendix I Table 1-3). In each case, we asked the participants to choose the maximum price that they were willing to pay to switch from the without to the with insurance revenue stream from the 12 price options provided below the table. They were not told what the underlying actuarially fair premium was.

In order to make farmers focus on the features of the hypothesized revenue flows we provided instead of on their own farming experience, we chose okra, which is rarely grown in that area, as the crop being portrayed the game. We assumed that farmers' revenues from growing okra follow a normal distribution with a mean of 15000 and a standard deviation of 5000 yuan. The 20-year revenue streams were drawn from the distribution. Note that we did not subtract the actuarially fair premium from the insured revenues, thus, those were first-order stochastic dominant to the uninsured. The insured revenue in year i was computed as follows:

$$rev_t^{ins} = max(rev_t, C * \overline{rev}), i = 1,2, \cdots ,20$$

where rev_t represents uninsured revenues in year t (in the right column), C is the coverage percent and $\overline{rev}$ stands for the sample mean of the uninsured revenues. The 12 price options were varied across coverage levels, taking on values from 0% to 180% of the actuarially fair premium in 20% increments. The actuarially fair premium is calculated as follows:

$$\pi^f = \frac{1}{20}\sum\nolimits_{t=1}^{20}(rev_t^{ins} - rev_t)$$

Regarding the experimental protocol, farmers were presented the table and then enumerators verbally described the key features of the revenue series to the farmers such as the values of the mean, the extreme values, the frequency of a covered revenue loss, and the maximum indemnity provided by the insurance contract. The participants were also told that the in order to secure the better (insured) revenue flow, they had to offer a price that was higher than the one we kept in secret, which was the fair value of the insurance. After the decisions were made, farmers were told whether or not they got the insurance revenue stream. If they didn't, a number t from 1 to 20 was drawn and 0.001 of the uninsured revenue at year t was paid to them. If they did, they received 0.001 of the insured revenue at year t minus the price they offered.

A trial game was played before the formal game in order to familiarize the farmers with the experimental protocol. The trial game included three rounds for each coverage level. All the procedures were exactly the same as in the formal game but the revenue streams were different and no payment was won. At the end of the formal game, we used a random incentive device to determine which of the three rounds the payment would be based on, in order to encourage the participants to be mindful of their decisions at all three coverage levels.

We were also interested in whether the insurance context affects farmers' choices. Therefore, we split the sample into two groups. In Group A, the participants were explicitly told that they were making the decision on a crop insurance product. In Group

B, a general decision-making context was described without any reference to insurance. Only two of the 236 of the farmers in this group, a handful gave indications that they had associated game with an insurance decision. In those cases, we explained that this was a research project with no insurance company involved, and we emphasized the rule of payment and that the participants should focus on the features of the game rather than thinking about insurance.

4.3.2 Risk Aversion Experiment

Following the WTP experiment, another experiment was conducted to elicit a measure of the individual's risk aversion level. The basic procedures of this game followed the design of Holt and Laury (HL) in 2002. We presented farmers a table (see Appendix II Table 4) with a set of pair-wise lotteries. For each line, the participant decided whether she preferred Lottery A or Lottery B. The enumerators verbally explained the table, pointing out that Lottery A had an unvarying payoff and Lottery B had an increasing payoff down to the list, and that participants were allowed to switch only once at most. We also explained that a random line on the table would be chosen ex post and the lottery they preferred at that line would be played for actual the game's stake. A trial game with exactly the same procedures but no payoff was played to help the participants become familiar with the decision-making process.

For the risk aversion measure, we assume the following power utility function:

$$v(y) = y^{\rho}$$

where the domain of ρ is $(0, \infty)$. A higher ρ implies that the participant is relatively less risk-averse, and individuals with $\rho = 1$ are risk neutral.

For a participant that switches at Line j, he or she prefers Lottery A to Lottery B at Line $j-1$ and prefers Lottery B to Lottery A at Line j. Take for example $j=2$, we have

$$0.7 * 5^{\rho} + 0.3 * 15^{\rho} > 0.9 * 2^{\rho} + 0.1 * 34^{\rho}$$

$$0.7 * 5^{\rho} + 0.3 * 15^{\rho} < 0.9 * 2^{\rho} + 0.1 * 38^{\rho}$$

The solutions to the two equations above yield a lower and an upper bound for the risk aversion coefficient associated with that individual as follows:

$$0.7 * 5^{\rho_U} + 0.3 * 15^{\rho_U} = 0.9 * 2^{\rho_U} + 0.1 * 34^{\rho_U}$$

$$0.7 * 5^{\rho_L} + 0.3 * 15^{\rho_L} = 0.9 * 2^{\rho_L} + 0.1 * 38^{\rho_L}$$

We also included two extra lines (Line 0 and Line 15) with a constant Lottery A and a lower/higher-payoff Lottery B to measure ρ individuals who never switched (always prefer Lottery A) or did so at Line 1 (always prefer Lottery B).

4.4 EMPIRICAL ESTIMATION METHODS

Our main empirical objective is to formulate a statistically model of WTP_i so that we can compute the probability of participation based on the equation. Conceptually $WTP_i = AFPE_i + RP_i$ and we note that both $AFPE_i$ and RP_i (and thus WTP_i) could be dependent on individual characteristics of the farmers and their farm operation as well as experimental design and insurance contract features. We develop an econometric model for $AFPE_i$ as well, in order to understand how farmers' expected AFP are affected by such explanatory factors.

Since the WTP experiment only yielded the bounds (WTP_{Li} and WTP_{Ui}) that presumably contain the WTP values for each of the farmers in the survey, those unobserved, latent values have to be estimated based on the bounds data. Thus, our empirical WTP model is defined as follows:

$$WTP_i = X_i\beta + e_i$$

where X_i is the $1\times k$ vector of values taken by the explanatory variables (possibly including an intercept) in the case of farmer i, β is a $k\times 1$ vector of unknown population parameters, and e_i is a random error term. Then:

$$Pr[WTP_{Li} < WTP_i \leq WTP_{Ui}] = Pr[WTP_{Li} < X_i\beta + e_i \leq WTP_{Ui}]$$

$$= Pr[WTP_{Li} - X_i\beta < e_i \leq WTP_{Ui} - X_i\beta]$$

$$= \Phi[WTP_{Li} - X_i\beta] - \Phi[WTP_{Ui} - X_i\beta]$$

where Φ is the cumulative distribution function (CDF) of the error term (e_i). In the context of the experiment, recall that although the incremental WTP choices presented to the farmers were expressed in Yuan, they were computed as proportions of the AFP underlying the choice.

Therefore, the WTP bounds are set as follows: If a farmer chose a) it implies that she would pay 0 but not 0.2 times AFP, thus $WTP_{Li} < WTP_i \leq WTP_{Ui}$ where WTP_{Li} is unknown and WTP_{Ui} is 0.20 times AFP. Note weallows negative WTP here considering the possibility thatrisk-lovingg individuals have to be paid to accept less risky income flow. If the farmer chose b) it implies that she would pay 0.20 times AFP but not 0.40 times AFP, thus WTP_{Li} is 0.20 and WTP_{Ui} is 0.40, and so on. Finally, if a farmer chose j) it implies that she would pay 1.80 times AFP or more; thus WTP_{Li} is 1.80 and WTP_{Ui} is unknown.

The last question to fully define $Pr[WTP_{Li} < WTP_i \leq WTP_{Ui}]$ is the choice for Φ. The simplest and most common is to assume that the error term distribution is normal with mean zero and variance $\sigma 2$. Since conceptually $WTP_i = AFPE_i + RP_i$, as detailed later, the distribution we assume for e_i will have implications for the distribution of the errors in AFP estimation by the farmers and thus for the probability that they purchase crop insurance. Therefore, in addition to normality, we will explore the possibility that the distribution of e_i is kurtotic and right or left skewed.

For that purpose, we use a modified version of the Johnson S_U family of distributions (Johnson, 1949) along the lines of Ramirez (1997). The distribution provides a system of curves with the flexibility to cover a wide variety of shapes. Specificall,y we assume the following CDF:

$$\Phi(z) = \phi[(\frac{ln\ (x + \sqrt{x^2+1})}{\theta}) - \mu]$$

where $x = (\frac{\theta z}{\sigma} + mc)$, $mc = -exp[\frac{1}{2}\theta^2 sinh(-\theta\mu)]$ and ϕ is a standard normal CDF[6]. Following similar derivations as in Ramirez (1997,) it can be shown (details available from the authors) that if $\mu = 0$, as θ approaches zero and Φ approaches $\phi(\frac{z}{\sigma})$ which in our modeling framework implies that the error term distribution is normal with mean zero and variance σ^2. On the other hand, if $\theta > 0$ and $\mu = 0$ the error term distribution is leptokurtic but symmetric, becoming right (left) skewed if μ is greater (less) than zero. Also it can show that regardless of the values of θ and μ the distribution has an expected value of zero and a variance that is proportional to σ^2. Thus, in both the normal and the non-normal models, heteroscedasticity can be incorporated by making the parameter σ a function of the variables that affect the error variance.

[6] In reference to the LLF $z = WTP_{Li} - X_i\beta$ for the first term and $WTP_{Ui} - X_i\beta$ for the second term.

In short, the advantages of this approach is that, since the normal CDF is nested to the S_U CDF, we can test whether the error term is normally distributed (Ho: $\theta = 0$ and $\mu = 0$), leptokurtic but symmetric (Ho: $\theta > 0$ while $\mu = 0$) and both leptokurtic and right or left-skewed (Ho: $\theta > 0$ and $\mu \neq 0$). In addition, as shown by Ramirez (2007), the S_U CDF is extremely flexible being able to accommodate any theoretically possible mean/variance/skewness/leptokurtosis combination and having the Gamma, Beta and Log-Normal distributions as limiting cases.

The other model to be estimated involves $AFPE_i$. As previously discussed, the second experiment yields lower- and upper-bounds for ρ_i (ρ_{Li} and ρ_{Ui}) which, given that the AFP underlying the WTP experiment choice is known, can be used to compute monetary lower- and upper-bound values for RP_i (RP_{Li} and RP_{Ui}).

$$\sum_{t=1}^{20} RS1_t^{\rho_{Ui}} = \sum_{t=1}^{20} (RS2_t - APF - RP_{Li})^{\rho_{Ui}}$$

and

$$\sum_{t=1}^{20} RS1_t^{\rho_{Li}} = \sum_{t=1}^{20} (RS2_t - APF - RP_{Ui})^{\rho_{Li}}$$

where $RS1$ and $RS2$ represent 20-year revenue streams without (Column 1 in tables of WTP Experiment) and with insurance (Column 2 in tables of WTP Experiment) respectively. In theory, WTP should be equal to the AFP corresponding to $RS2$ (which is known to the researcher conducting the experiment) plus the risk premium of that particular individual. Therefore, RP_{Li} and RP_{Ui} can be implicitly inferred respectively.

In turn, as in the case of RP_i, those values can be rescaled to proportions of the underlying AFP. For example, rescaled RP_i bounds of -0.22 to 0.10 imply that the risk premium for that particular farmer is between -22% and 10% of the AFP. Given that WTP_i= $AFPE_i + RP_i$, the corresponding $AFPE_i$ bounds are computed as follows:

$$AFPE_{Li} = WTP_{Li} - RP_{Ui}$$

$$AFPE_{Ui} = WTP_{Ui} - RP_{Ui}$$

The $AFPE_i$ model is estimated using those bounds as the dependent variable and the same econometric procedures applied in the case of the WTP_i model. Similar to WTP_i censoring, $AFPE_{Li}$ is left-censored if farmer i chooses zero and WTP_{Ui} is right-censored if farmer i chooses 1.8.

4.5 EMPIRICAL RESULTS

4.5.1 Willingness to Pay (WTP) Model

First, a homoscedastic, normal-error willingness to pay model is estimated that includes dummy intercept shifters for the coverage level, the experimental setting, gender, and the willingness to purchase insurance, as well as age, years of education, a measure of the average propensity to consume[7], and the risk aversion coefficient[8].

After exploring various functional forms for the variables, it is concluded through a combination of t and F tests that four of those variables are not significant ($\alpha = 0.25$) and that the risk aversion coefficient is non-linearly related to WTP (See Appendix III Table 5). The resulting model (Table 4.1) suggests that these respondents place a significantly higher value on the low coverage than on the high coverage. In addition, farmers' WTP is lower when the experiment is framed as an insurance decision and higher for females, more educated respondents, and those who later indicated they purchase or would like to

[7] Measured as the percentage (0%=0 10%=1,…, 100%=10) of income (10,000 Yuan) that the respondents indicated would be used for consumption.
[8] Computed by the average of the two bounds elicited from each farmer in the second experiment (H&L experiment).

purchase crop insurance. Also as expected, the average propensity to consume parameter estimate is negative. Finally note that the best functional form to relate risk aversion with WTP includes a linear, a reciprocal, and a square root term.

In order to ascertain whether the other parameters are invariant relative to the insurance versus not insurance framing and the three different coverage levels we estimate six separate sub-models (See Appendix III Table 6), one for each categorical combination, and conduct a likelihood ratio test of the restricted model (Table 4.1) versus those six sub-models which jointly constitute the unrestricted model. The cross-model parameter restrictions cannot be rejected at an $\alpha = 0.25$ leading us to conclude that the more parsimonious restricted model is preferred.

The next level of complexity is to allow for the possibility that the error term is heteroskedastic and/or not normally distributed, using the methods outlined in the previous section. The added non-normality parameters are both highly significant according to the t and likelihood ratio tests. Positive θ and μ parameters indicate that the error distribution is leptokurtic and right-skewed, and the error variance is lower for the highest (90%) coverage level and in the case where farmers were told that the experiment was related to an insurance decision. All other variables included in the error-variance equation were statistically insignificant ($\alpha = 0.25$).

The estimates for the parameters corresponding to the explanatory variables are almost identical to those in the homoscedastic normal error model in terms of signs, magnitudes and statistical significance[9] (Table 4.1). Note that since the willingness to pay

[9] As previously indicated, the variance parameter(s) in the non-normal model are only proportional to the error term variance and thus their magnitudes are not directly comparable with those of the normal model. As well, variance estimates can change substantially when a non-normal distribution is assumed since the overall level of dispersion can also be affected by skewness and kurtosis.

is being measured as a fraction of the actuarially fair premium, the parameter estimates have a fairly natural interpretation. However, it is relative to an AFP of 1, the WTP is predicted to be substantially lower (-0.183 and -0.301) for the higher (60% and 90%) coverage levels, as well as when the experiment is framed as being about insurance (-0.185). Females are predicted to have a (0.062) higher WTP as well as those who are more educated (0.042 per unit of increase in the level of education). Farmers who do or would like to buy insurance are willing to pay more (0.135) while those with higher average propensity to consume are willing to pay less (-0.012 for each 10% increase in the APC).

The within sample WTP predictions from this model average 0.774 and range from 0.299 to 1.293 versus 0.737 and 0.241 to 1.323 in the case of the normal model. This means the respondents are willing to pay between 29.9% and 129.3% of the AFP, and only 77.4% on average. However, this varies widely depending on the coverage level and the way the experiment was framed. When the experiment was framed as an insurance decision, the average WTPs are 83.1% of the AFP at the 30% coverage level, 64.28% at the 60% level, and 53.0% at the 90% level. As shown later, these predictions have dire implications regarding the expected levels of farmer interest in purchasing this particular type of crop insurance.

4.5.2 Actuarially Fair Premium Estimate Model

The dependent variable in this model are the bounds for the actuarially fair premium estimate ($AFPE_{Li}$ and $AFPE_{Ui}$) which, as previously detailed, were computed on the basis of the willingness to pay bounds (WTP_{Li} and WTP_{Ui}) elicited from the first experiment and the risk premium bounds (RP_{Li} and RP_{Ui}) corresponding to the risk aversion coefficient bounds (ρ_{Li} and ρ_{Ui}) elicited from the second experiment. As well, we follow the same econometric identification and estimation strategies utilized for the WTP model.

As in the case of the WTP model, the error term non-normality parameters are statistically significant ($\alpha = 0.01$) indicating leptokurtosis and right-skewness and its variance depends on several explanatory factors, specifically, it is lower at the highest (90%) coverage level, when the WTP experiment was framed as insurance and for the more educated respondents but positively related to the average propensity to consume (Table 4.2). Regarding the mean effects, relative to an AFP of 1, the AFPE are lower (-0.0727 and -0.1280) at the higher coverage levels (60% and 90%), when the experiment was framed as insurance (-0.1824), and at the higher average propensities to consume. On the other hand, female respondents and those who indicated they purchase or would be willing to purchase insurance exhibit higher AFPEs (0.0829 and 0.1564 respectively). The best functional form to relate risk aversion with the actuarially fair premium estimates only includes a linear and a reciprocal term.

4.5.3 WTP, AFPE and Risk Aversion

The fact that the risk aversion coefficient is found to have a highly significant effect on the WTP as well as the AFPE is an interesting finding. This suggests that risk aversion may affect the WTP not only through the risk premium, but that the farmers' implicit estimates of the fair value of the insurance contract might be influenced by their levels of risk aversion as well.

The range of the risk aversion coefficient measure (ρ_i) observed in the experiment is from 0.30 (very risk-averse) to 1.6 (highly risk-loving), with an average very close to

1.0 (risk neutral) (see Table 4.3 for details). Figure 4.2 shows the predicted relationships between the risk aversion coefficient and the WTP and AFPE at a baseline where all the other explanatory variables are set to zero, as well as the difference between the two which is the relative risk premium (RP) corresponding to that level of risk aversion.

Notably, the maximum WTP is at $\rho_i = 0.50$, which means that very risk-averse respondents ($0.30 < \rho_i < 0.50$) have lower WTPs. WTP is predicted to decline from $\rho_i = 0.50$ to 1.50 and then levels off. While it seems counter-intuitive for veryrisk-aversee farmers to have lower WTPs, as previously noted, this might be caused by the effect of risk aversion on the AFPE, which is predicted to be monotonically increasing (Figure 4.2). This suggests that the more risk-averse farmers revealed much more conservative estimates of the AFP than the risk-loving individuals. The RP relation implied by these WTP and AFPE predictions ($RP = WTP - AFPE$) is also depicted in Figure 4.2. As expected, this relationship is monotonically decreasing reaching a maximum of $RP = 70\%$ of the AFP at $\rho_i = 0.30$ and rapidly declines for lessrisk-aversee behavior. Negative risk premiums down to -23.6% are predicted for the most risk-loving individuals ($\rho_i = 1.80$). Also note that the WTP, AFPE and RP predictions depicted in Figure 4.2 are contingent on and would thus shift vertically depending on the values taken by the explanatory variables in the models.

4.5.4 Participation Predictions

Predictions for the percentage of farmers expected to purchase crop insurance under different conditions can be made based on the estimated models and the probabilistic relationships established in the conceptual framework, specifically: $P_i = Pr[WTP_i > AFP]$. Since the estimated model is $WTP_i = X_i\hat{\beta} + \hat{e}_i = \widehat{WTP}_i + \hat{e}_i$:

$$P_i = Pr[WTP_i > (1-s)AFP] = Pr[\widehat{WTP}_i + \hat{e}_i > (1-s)AFP]$$

$$= Pr[\hat{e}_i > (1-s)AFP - \widehat{WTP}_i] = \Phi((1-s)AFP - \widehat{WTP}_i)$$

where $\widehat{\mathrm{WTP}}_i$ represents the point predictions from the WTP model, $\hat{e}_i$ is the model's residual term and s is the subsidy rate. Given s, AFP and that $\widehat{WTP}_i = X_i\hat{\beta}$, the above probability can be calculated at the parameter estimates for the error term distribution (θ, μ and σ). This reflects the fact that the true WTP is not known with certainty and $\widehat{WTP}_i$ is an estimate measured with a significant degree of error. Thus, a (potentially) different probability of participation for each in individual i in the sample is computed.

As previously stated, AFP will depend on the method used by the insurer to obtain individual farmer-level premium estimates. The generalized practice in China's crop insurance program is to charge every farmer the same fixed amount per unit of area for a given coverage level. Thus, if we assume that the vegetable production systems in that region are fairly homogeneous (i.e., their underlying AFPs are about the same) and the insurer provides AFP insurance contract.

For the entire sample of 477 respondents evaluated at the actual values of the explanatory factors in the model the WTP predictions average 0.808 and range from 0.307 to 1.335 of the AFP, and only 17.8% of the predictions exceed the AFP of 1 (See Figure 4.3). The computed probabilities of participation ($Pr[\widehat{WTP}_i > 1] = \Phi(1 - \widehat{WTP}_i)$) average 33.9% and range from 10.3% to 72.3%, with only 11.6% of the respondents exhibiting a probability of participation of more than 50% (See Figure 4.4).

Since around 52% of the sample contains WTP responses of individuals who played the experiment under an insurance frame, and the WTPs were substantially lower for the other 48% for whom the experiment was framed as a neutral frame decision. For a more realistic analysis, it makes sense to predict the 1431 probabilities setting the dummy variable for "experiment was framed as insurance" equal to one. As well, the dummy variables for coverage level can be set to obtain predictions for 30%, 60% and 90% coverage scenarios.

The WTP predictions under the "framed as insurance" scenario and a 30% coverage level average 0.880 and range from 0.608 to 1.176 of the AFP, and 13.5% of the predictions exceed the AFP of 1. The computed probabilities of participation average 42.1% and range from 25.4% to 61.7%. In short, at the lowest coverage level of 30%, it is expected that less than 1/3rd of the farmers would purchase vegetable insurance if it was offered at the actuarially fair premium. At the 60% coverage level the WTP predictions average 0.697 and range from 0.425 to 0.993 of the AFP. The computed probabilities of participation average 30.1% and range from 16.5% to 49.5%. At the 90% coverage level the WTP predictions average 0.579 and range from 0.307 to 0.875 of the AFP. The computed probabilities of participation average 24.2% and range from 12.1% to 41.6%. Table 4.4 shows the willingness to pay and associated predicted participation rate under the three coverage scenarios. As expected given the estimated model parameters, without subsidies, the probabilities of participation decline substantially at higher coverage levels.

Next we explore what would happen if a 50% subsidy was provided, i.e. the farmers would only have to pay half of what is actuarially fair. At the 30% coverage level, the average probability of participation increases to 73.7%. The average probability of participation declines to 62.9% at 60% coverage and 55.2% at the highest 90% coverage level. Table 4.5 shows the predicted participation rate with 50% subsidy under the three coverage scenarios.

The above analyses assume 1) the AFPs are the same for all farmers and 2) the insurer provides AFP insurance contracts. The second assumption is not that critical in the presence of subsidies. For example, if the insurer overestimates the AFP by 20% but offers a 50% subsidy, the farmers would be facing uniform premiums that are 60% of their AFPs. Obviously, in this case, the predicted probabilities of participation would also overestimate what is likely to occur in practice. In such a scenario, the model's predictions would be more useful to ascertain the change in the probabilities of participation if the subsidy level was to be adjusted.

The impact of violating the first assumption that the AFPs are the same for all farmers can be explored by randomly varying premium rate. Mathematically, this is equivalent to assuming random variations in the farmers' crop revenue and resulting AFPs. For example, let the average AFP across all farmers' ($\overline{AFP}$) be equal to 1. Under a 50% subsidy all famers would be offered a premium of 0.50. Then assume that the lowest risk farmer has an AFP of $AFPi = 0.50\overline{AFP} = 0.5$. In such a scenario, that farmer would face a premium offer that is exactly the same as his/her individual AFP. Alternatively, assume that the highest risk farmer has an AFP of $AFP_i = 1.5\overline{AFP} = 1.5$. In such a scenario, that farmer would face a premium offer that is only 1/3rd of her individual AFP. Therefore, if the individual farmer AFPs uniformly range from 0.50 to 1.5 of the average, in our computations, this is mathematically equivalent to uniformly varying the premium offer (AFP) from 0.333 to 1.

The average, minimum and maximum probabilities of participation for this scenario are also presented in Table 4.6. Notably, across coverage levels, they are significantly lower than when all farmers are assumed to have the same AFP. In other words, the 50%

subsidy is not as effective on inducing participation when there is substantial variability in the farmers' AFPs. Overall, it can be concluded that under an average effective subsidy of 50%, depending on the degree of variation in the farmers' risk profiles, participation rates would range from 27.7% to 88.9% at the 30% coverage level, 18.9% to 83.2% at 60%, and 15.1% to 77.5% at the 90% coverage level. The upper limits are unlikely, however, since at least a moderate spread is expected in the underlying AFPs.

When the AFPs are assumed to be homogeneous across farmers, the normal model consistently overestimates participation rates by as much as 11% at the 90% coverage level. Similarly, high levels of overestimation are observed when the underlying AFPs are assumed to range from 0.50 to 1.5. Interestingly, while the minimum probabilities as generally overestimated by the normal error model as well, the maximum probabilities are underestimated in all cases, by as much as 10%.

4.6 CONCLUSION

In order to model the unexpectedly suboptimal take-up of crop insurance in developing countries, we propose a probabilistic model, which explicitly recognizes that farmers are uncertain about the exact value of the actuarially fair premium (AFP) underlying the desired policy. Farmers are supposed to be uncertain about their AFP due to various reasons, such as their limited experience in and knowledge on insurance, trust issues, or even liquidity constraint. As a result of such uncertainty, some rational individuals might not purchase insurance even if they are risk-averse and their premiums are highly subsidized. Once the possibility that crop insurance premiums may be biased for some farmers is incorporated, then certain anomalies surrounding farmers' crop insurance choices may be partly explained.

Using data from field experiments with 477 vegetable farmers in China, our probabilistic model suggests that farmers place a significantly higher value on the low coverage than on the high coverage. In other words, low coverage contracts are likely to be more salable in an emerging insurance market. In addition, farmers' WTP is lower when they face an insurance decision than a neutral frame lottery. The negative effect of insurance frame may be explained by trust issues, limited knowledge on insurance or unpleasant experience in purchasing insurance in the past. In terms of individual characteristic, females and more educated farmers are willing to pay a higher price for insurance. Also as expected, the average propensity to consume parameter estimate is negative. We also investigate the factors that affect farmers' actuarially fair premium estimate. Similar to the results of WTP model, the AFPE are lower at the higher coverage levels, for insurance frame contracts, and at the higher average propensities to consume. On the other hand, female respondents and those who indicated they purchase or would be willing to purchase insurance exhibit higher AFPEs. Our data also shows that the risk aversion coefficient is found to have a highly significant effect on the WTP as well as the AFPE. This suggests that risk aversion may affect the WTP not only through the risk premium, but farmers' estimate of fair value of the insurance contract as well. Finally, the probabilistic model is able to predict how the performance of the crop insurance program (i.e., the participation rate, the overall program subsidy to the government, the resulting distribution of the subsidies across participating farmers, etc.) would be affected by changes in the premium subsidy rates.

Table 4.1 Willingness to Pay Models with the Normal and Non-Normal Errors

	(1) Normal Errors	(2) Non-Normal Errors
Coverage level=60%	-0.243***	-0.183***
	(0.038)	(0.028)
Coverage level=90%	-0.326***	-0.301***
	(0.037)	(0.035)
Frame (Insurance=1)	-0.172***	-0.185***
	(0.032)	(0.032)
Gender (Female=1)	0.107***	0.062***
	(0.031)	(0.024)
Education	0.040*	0.042***
	(0.020)	(0.015)
Buy Insurance	0.128***	0.135***
(Yes=1)	(0.033)	(0.025)
APC	-0.016***	-0.012***
	(0.005)	(0.004)
RAC	5.265*	2.749**
	(2.738)	(1.078)
$1/RAC$	-1.114**	-0.688***
	(0.460)	(0.214)
$\sqrt{RAC}$	-13.483**	-7.495***
	(6.575)	(2.753)
Constant	10.228**	6.386***
	(4.270)	(1.878)
Sigma	0.591***	0.217***
Sigma Insurance Frame	-0.050	-0.030***
Sigma Coverage level=90%	-0.072	-0.034***
θ	-	0.543***
μ	-	2.942***
2MLLV=	-6320.63	-6195.48

Notes: The dependent variables are the price interval of WTP and the explanatory variable labels (in order) denote dummy variables of the 60% and 90% coverage levels, the experiment being framed as insurance, gender=female, years of education (takes the values of 3, 6, 9, 12 or 18), whether the farmer purchases or indicated willingness to purchase insurance if it was made available, the average propensity to consume (APC), and linear, reciprocal and square root functions of the risk aversion coefficient (RAC). Then Sigma denotes a constant error term variance parameter, followed by dummy variables for the 90% coverage level and the experiment being framed as insurance in the error variance equation. θ denotes kurtosis and μ denotes skewness. The 2MLLV denotes twice the maximum value of the log-likelihood function.

The number of observations is 1431, where 176 are left-censored observations, 63 are right-censored observations and 1183 are interval observations.

Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2 Actuarially Fair Premium Estimate Models with Normal and Non-Normal Errors

	(1) Normal Errors	(2) Non-Normal Errors
Coverage level=60%	-0.115^{***}	-0.073
	(0.040)	(0.047)
Coverage level=90%	-0.115^{***}	-0.128^{***}
	(0.039)	(0.042)
Frame (Insurance=1)	-0.177^{***}	-0.182^{***}
	(0.033)	(0.041)
Gender (Female=1)	0.100^{***}	0.083^{**}
	(0.032)	(0.034)
Buy Insurance	0.129^{***}	0.156^{***}
(Yes=1)	(0.034)	(0.036)
APC	-0.016^{***}	-0.013^{**}
	(0.006)	(0.006)
RAC	0.287^{**}	0.140^{*}
	(0.121)	(0.078)
$1/RAC$	-0.327^{***}	-0.301^{***}
	(0.057)	(0.044)
Constant	1.006^{***}	1.049^{***}
	(0.215)	(0.166)
Sigma	$.689^{***}$	0.260^{***}
Sigma Insurance Frame	-0.085^{*}	-0.048^{***}
Sigma Coverage level=90%	-0.038	-0.093^{***}
Sigma Education	-0.059^{**}	-0.013^{***}
Sigma APC	0.010	0.002^{*}
θ	-	0.228^{***}
μ	-	8.881^{***}
2MLLV=	-6380.637	-5881.538

Notes: The dependent variables are the price interval of AFP estimate and the explanatory variable labels (in order) denote dummy variables of the 60% and 90% coverage levels, the experiment being framed as insurance, gender=female, whether the farmer purchases or indicated willingness to purchase insurance if it was made available, the average propensity to consume (APC), and linear and reciprocal functions of the risk aversion coefficient (RAC). Then Sigma denotes a constant error term variance parameter, followed by the experiment being framed as insurance, dummy variables for the 90% coverage level, years of education (takes the values of 3, 6, 9, 12 or 18) and APC in the error variance equation. θ denotes kurtosis and μ denotes skewness. The 2MLLV denotes twice the maximum value of the log-likelihood function.

The number of observations is 1431, where 176 are left-censored observations, 63 are right-censored observations and 1183 are interval observations.

Significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3 Summary Statistics of Risk Aversion Coefficient

Variable	Mean	Std. Dev.	Min	Max
Risk Aversion Coefficient	0.89	0.53	0.33	1.49
Lower Bound of RAC	0.85	0.47	0.34	1.35
Upper Bound of RAC	0.93	0.60	0.31	1.64

Table 4.4 Summary Statistics of Predicted WTP and Participation Rate by Coverage Level

	Mean	Std. Dev.	Min	Max
WTP 30%	0.88	0.11	0.61	1.18
Participation Rate 30%	0.42	0.07	0.25	0.62
WTP 60%	0.70	0.11	0.43	0.99
Participation Rate 60%	0.31	0.06	0.17	0.50
WTP 90%	0.58	0.11	0.31	0.87
Participation Rate 90%	0.24	0.06	0.12	0.42

Table 4.5 Summary Statistics of Participation Rate with 50% Subsidy

	Mean	Std. Dev.	Min	Max
Participation Rate 30%	0.74	0.06	0.57	0.87
Participation Rate 60%	0.63	0.07	0.45	0.80
Participation Rate 90%	0.55	0.07	0.37	0.74

Table 4.6 Summary Statistics of Participation Rate with 50% Subsidy and Random AFP

	Mean	Std. Dev.	Min	Max
Participation Rate 30%	0.63	0.13	0.28	0.89
Participation Rate 60%	0.52	0.14	0.19	0.83
Participation Rate 90%	0.45	0.14	0.15	0.78

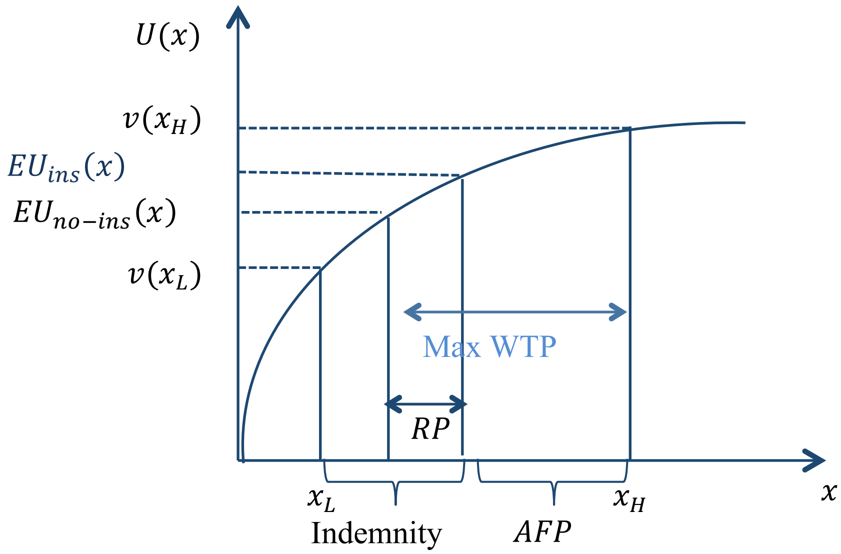

Figure 4.1 Risk Premium (RP) and Willingness to Pay (WTP)

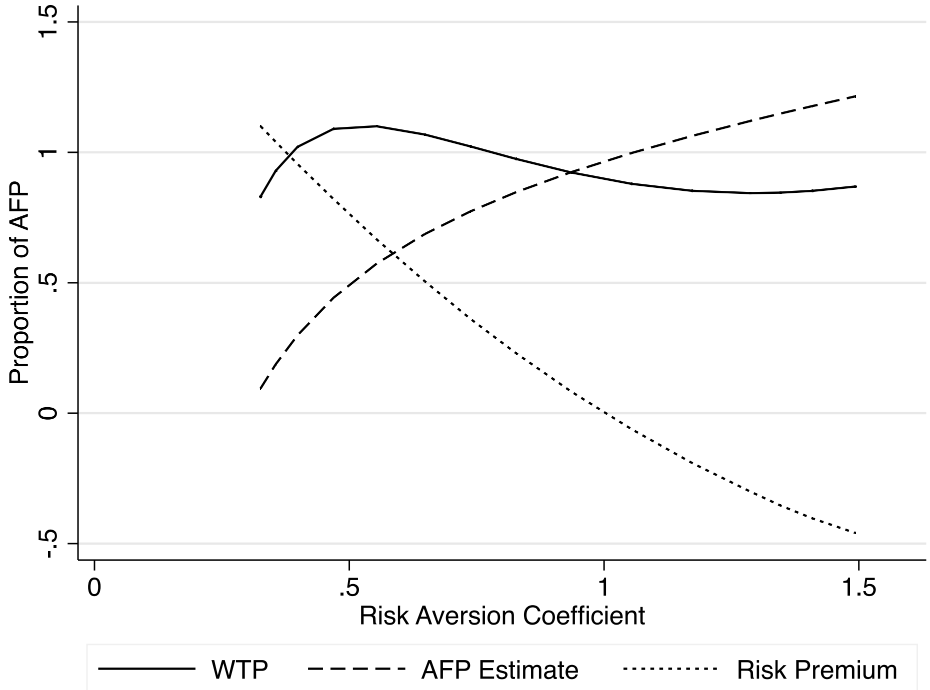

Figure 4.2 WTP, AFP Estimate and Risk Premium

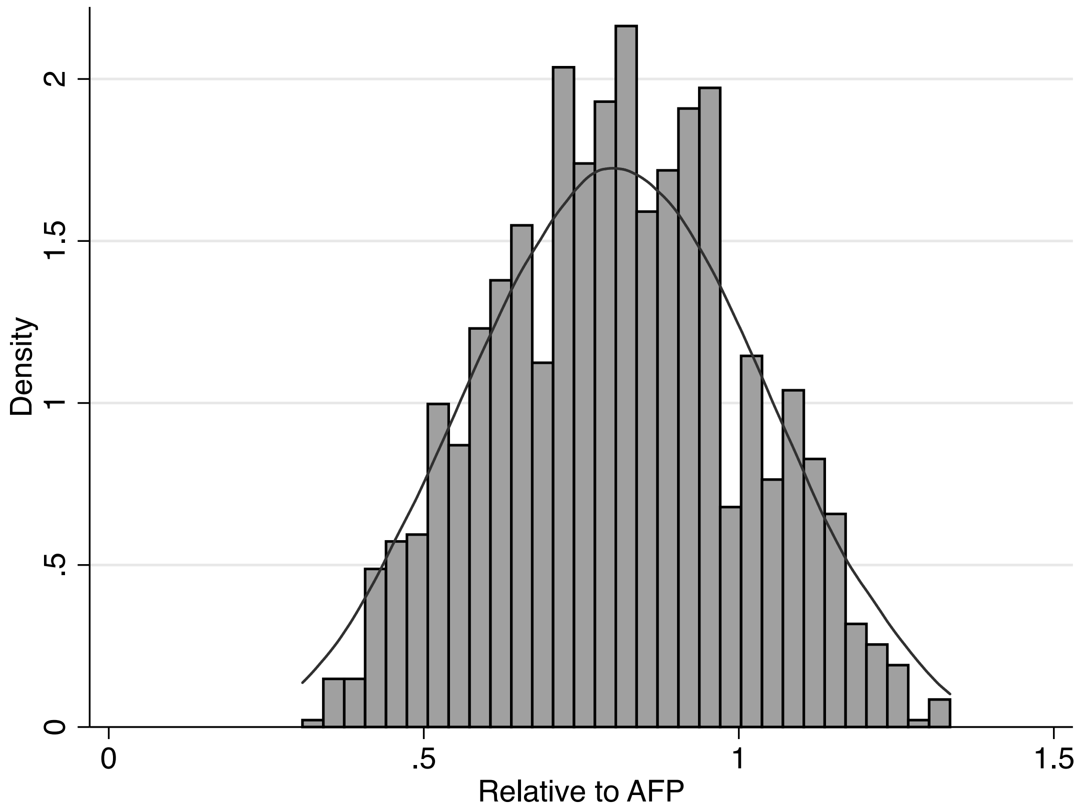

Figure 4.3 Predicted WTP

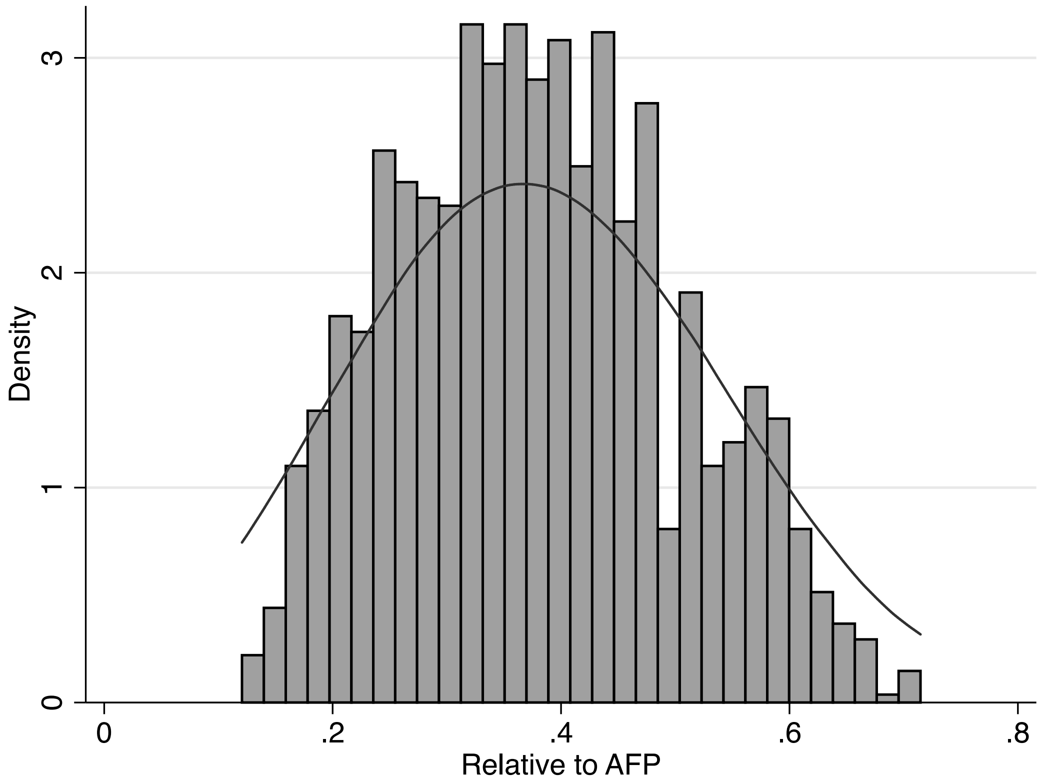

Figure 4.4 Predicted Participation Rate by WTP model

BIBLIOGRAPHY

Cai, J. and Song, C., 2017. Do Disaster Experience and Knowledge Affect Insurance Take-up Decisions? *Journal of Development Economics*, 124, pp.83-94.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J., 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics*, 5(1), pp.104-35.

Cole, S., Stein, D. and Tobacman, J., 2014. Dynamics of Demand for Index Insurance: Evidence from a Long-Run Field Experiment. *American Economic Review*, 104(5), pp.284-90.

Dercon, S., Hill, R.V., Clarke, D., Outes-Leon, I. and Taffesse, A.S., 2014. Offering Rainfall Insurance to Informal Insurance Groups: Evidence From a Field Experiment in Ethiopia. *Journal of Development Economics,* 106, pp.132-143.

Du, X., Feng, H. and Hennessy, D.A., 2016. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics*, 99(3), pp.732-756.

Giné, X., Townsend, R. and Vickery, J., 2007. Patterns of Rainfall Insurance Participation in Rural India. *The World Bank.*

Just, R.E., Calvin, L. and Quiggin, J., 1999. Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives. *American Journal of Agricultural Economics*, 81(4), pp.834-849.

Karlan, D., Kutsoati, E., McMillan, M. and Udry, C., 2011. Crop Price Indemnified Loans for Farmers: A Pilot Experiment in Rural Ghana. *Journal of Risk and Insurance,* 78(1), pp.37-55.

Lybbert, T.J., Galarza, F.B., McPeak, J., Barrett, C.B., Boucher, S.R., Carter, M.R., Chantarat, S., Fadlaoui, A. and Mude, A., 2010. Dynamic Field Experiments in Development Economics: Risk Valuation in Morocco, Kenya, and Peru. *Agricultural and Resource Economics Review*, 39(2), pp.176-192.

Miranda, M.J., 1991. Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics,* 73(2), pp.233-242.

Mishra, A.K. and Goodwin, B.K., 2006. Revenue Insurance Purchase Decisions of Farmers. *Applied Economics,* 38(2), pp.149-159.

Morduch, J., 1995. Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives*, 9(3), pp.103-114.

Ramirez, O.A. 1997. "Estimation and Use of a Multivariate Parametric Model for Simulating, Heteroskedastic, Correlated, Nonnormal Random Variables: The Case of Corn Belt Corn, Soybean and Wheat Yields." *American Journal of Agricultural Economics* 79(1):191–205

Ramirez, O.A. and Shonkwiler, J.S., 2017. A Probabilistic Model of Crop Insurance Purchase Decision. *Journal of Agricultural and Resource Economics*, 42(1835-2016-149594), p.10.

Ramirez, O.A., Carpio, C.E. and Collart, A.J., 2015. Are the Federal Crop Insurance Subsidies Equitably Distributed? Evidence from a Monte Carlo Simulation Analysis. *Journal of Agricultural And Resource Economics,* pp.457-475.

Ramirez, O.A., Carpio, C.E. and Rejesus, R.M., 2011. Can Crop Insurance Premiums Be Reliably Estimated? *Agricultural and Resource Economics Review,* 40(1), pp.81-94.

Review 39(2): 176-192 (2010)

Sherrick, B.J., Barry, P.J., Ellinger, P.N. and Schnitkey, G.D., 2004. Factors Influencing Farmers' Crop Insurance Decisions. *American Journal of Agricultural Economics,* 86(1), pp.103-114.

Xavier Giné, Robert Townsend, James Vickery; Patterns of Rainfall Insurance Participation in Rural India, *The World Bank Economic Review*, Volume 22, Issue 3, 1 January 2008, Pages 539–566,

CHAPTER 5

SUMMARY AND CONCLUSIONS

Lack of disaster risk protection mechanisms in developing markets has proven to be a significant hurdle to developing sustainable farm safety nets. Why farmers have low spontaneous desire to purchase crop insurance and potential institutional, policy, and outreach efforts to overcome barriers to crop insurance adoption, have been active areas of research since 1990s.

This dissertation examines anomalies in crop insurance choices of smallholder farmers in emerging crop insurance markets based on a series of surveys and experiments with 477 vegetable farmers in China. Some of the anomalous choices have been discussed in previous studies. Other anomalies disclosed in this study are less explored. First, to assess farmers' intrinsic resistance to crop insurance potentially due to negative opinions or confidence in the risk management approach, we use an unique experiment to examine farmers' decisions framed both in an insurance context and in a neutral frame without mentioning the name of insurance. We found that farmers place approximately 20% less value for an insurance contract than an equivalent risk-reducing contract with a neural frame. Second, unlike previous studies exploring farmers' insurance take-up decision, we examine farmers' insurance coverage choices. Our data shows that, with other things equal, farmers are more willing to purchase low coverage than high coverage, even when all the coverage levels are priced at actuarially fair values and the high coverage can provide farmers more monetary transferring from government-like institutions. Furthermore, this study investigates the impact of loss aversion, which has been discussed in prior studies. Our results suggest that risk averse and loss averse farmers, who are theoretically supposed to be more interested in adopting risk protection tools, have less willingness to purchase high coverage insurance.

Taken the anomalous choices together, in the third chapter, we propose a model framework to explain farmers' choices. We posit that farmers are narrow framers, who tend to view crop insurance as an investment independent from other risks. Under such assumption, prospect theory does a better job at explaining smallholder farmers' crop insurance choices than conventional theory that assumes individuals are rational. Indeed, the narrow framing assumption may be at odds with the purpose of buying insurance-seeking to risk protection. However, farmers in our data live in rural areas of developing countries, and usually have less experience in purchasing insurance. Thus, they probably tent to view crop insurance as an innovative technology or investment rather than a risk-transferring tool. Another possible explanation of narrow framing is that under imperfect market conditions, where trust issues, lack of insurance knowledge and incomplete information are prevalent, farmers usually hold a conservative opinion toward crop insurance. This means farmers view status quo with zero insurance as their reference point. As a result of the narrow framing, a sense of loss is felt when farmer pay insurance premium and no indemnity gained in a year of no crop loss. The narrow framing assumptions can explain why loss aversion and risk aversion have negative association with insurance take-up and coverage choice.

In the fourth chapter, we provide an innovative probabilistic model to predict farmers' choice. Unlike previous efforts to explore the reasons for low take-up or test some specific barriers, our study focus on a mathematical framework to model farmers' demand with uncertainty. Most previous studies on farmers' demand for crop insurance implicitly or explicitly assume that farmers know the actuarially fair premium with certainly. However, there is no statutory requirement that the premium set at the individual level be such. Once we relax the assumption and consider a probabilistic model, which explicitly recognizes that farmers are uncertain about the exact value of the actuarially fair premium (AFP) underlying the desired policy, some rational individuals might not purchase insurance even if they are risk-averse and their premiums are highly subsidized. More importantly, the model can to anticipate the probability of participation in a target area given a certain subsidy level. The results of our model suggests that farmers' estimate of AFP is lower for high coverage level than low coverage level and is lower for a contract that is framed as insurance. In addition, more educated and female farmers are willing to a pay higher price for crop insurance.

The findings of this dissertation emphasize the importance of building a benign market environment for the development of crop insurance programs in developing countries. When the market is not perfectly developed, farmers usually hold negative opinions toward insurance due to lack of trust, lack of confidence of insurance contract implement or high transaction cost. These negative opinions give rise to the multiple distortions in crop insurance demand. Under such circumstance, low coverage insurance contracts are more salable than the high coverage, and farmers with less risk aversion and less loss aversion are likely to purchase insurance. Moreover, we find that providing high subsidy seems not a panacea for the problem of the negative opinions and the demand distortions. In particular, risk averse and loss averse farmers may not reap as much the subsidy benefits as do their peers with low risk aversion and loss aversion.

APPENDIX

Appendix I-Information on the Current MPCI

Table a-1. Summary of the pricing of insurance

<table>
<tr><th>Vegetable</th><th>Farming technique</th><th>Maximum indemnity (yuan/unit)</th><th>Probability of disaster (premium in percent)</th><th colspan="2">Premium in amount (yuan/unit)</th><th colspan="2">Premium paid by farmers (yuan/unit)</th></tr>
<tr><td>Watermelon</td><td>Open field</td><td>1500</td><td>10%</td><td colspan="2">150</td><td colspan="2">30</td></tr>
<tr><td rowspan="3">Stem, root, and leaf vegetable (e.g., carrot, radish, lettuce, spinach, broccoli, etc.)</td><td rowspan="3">Open field</td><td>1000 for late spring harvest</td><td>6%</td><td colspan="2">60</td><td colspan="2">12</td></tr>
<tr><td>800 for summer or fall harvest</td><td>6%</td><td colspan="2">48</td><td colspan="2">9.6</td></tr>
<tr><td>1800 for a whole year</td><td>5%</td><td colspan="2">90</td><td colspan="2">18</td></tr>
<tr><td rowspan="3">Fruit vegetable (e.g., tomato, eggplant, green pepper, pumpkin, etc.)</td><td rowspan="3">Open field</td><td>1200 for late spring harvest</td><td>6%</td><td colspan="2">72</td><td colspan="2">14.4</td></tr>
<tr><td>1000 for summer or fall harvest</td><td>6%</td><td colspan="2">60</td><td colspan="2">12</td></tr>
<tr><td>2200 for a whole year</td><td>5%</td><td colspan="2">110</td><td colspan="2">22</td></tr>
<tr><td rowspan="3">Vegetable, melon, and fruit</td><td rowspan="3">Greenhouse</td><td>10000 for structure</td><td>12‰</td><td rowspan="3">480 for one year</td><td rowspan="3">288 for 1/2 year</td><td rowspan="3">96 for one year</td><td rowspan="3">57.6 for 1/2 year</td></tr>
<tr><td>1200 for film</td><td>20%</td></tr>
<tr><td>3000 for crop</td><td>4%</td></tr>
</table>

Note: The numbers are based on the insurance contracts in 2017.

Appendix II-Questionnaire

Questionnaire for Farmers' Demand for Vegetable Insurance in China

County Code:

Village Code:

Household Code:

Household Name & phone No.:

Enumerator Code, Name & phone No.:

Date of Survey:

Please ensure that the respondent of this survey is the production decision maker of the household

The enumerator fills the following questions completely and accurately according to the answer of the respondent

Part I: Basic Information

Q1. Name & Contact Number:

Q2. Age:

Q3. Education:

A. 0 Years.

B. Preliminary School/ 1-6 years.

C. Middle School/7-9 years.

D. High School or equivalent (such as vocational school)/10-12 year.

E. College or Undergraduate/13-17 years.

F. Graduate or higher/ over 18 years.

Q4. Please check all the items you owned.

a. Productive capital

☐ van ☐ truck ☐ electronic automobile ☐ small farm machinery

b. Durable goods

☐ smart cellphone ☐ feature cellphone ☐ wired internet access ☐ wireless internet access (WIFI) ☐ television ☐ refrigerator ☐ air conditioner ☐ electronic fans ☐ electronic fans ☐ washing machine ☐ car ☐ electronic bicycle ☐ bicycle ☐ calorifier (for shower)

c. How many real estates you own?

Q5. How much does profit from vegetable production comprise your annual income?

A. Over 90%
B. Around 80%

C. Around 70%
D. Around 60%
E. Around 50%
F. Around 40%
G. Around 30%
H. Around 20%
I. Below 10%

Part II: Production information

Q1. The acreage of land you grow (including grain/fruit/vegetable) is __(mu).

Q2. The acreage of land you grow vegetable is _(mu), where _(mu) in greenhouse, and (mu) in the field.

Q3. How many years do you grow vegetable?

Q4. How many types of vegetable do you grow for the purpose of profit in 2017?

Q5. List all the (or the four most major) vegetable you grow for the purpose of profit in 2017

	1	2	3	4
Vegetable/fruit (ordered by acres from most to least)				

(Code: A1= Watermelon, A2=muskmelon, A3=grape, A4=other types of fruit not included in A1-3. B1=eggplant, B2=Tomato, B3=Cucumber, B4=Green pepper, B5=Green-leaf vegetable, B6=Kidney beans B7=other types of vegetable not included in B1-6)

Q6. Fill the table of Benefit-Cost for vegetable

(The benefits and costs are supposed to be average in recent 3 years. Please take the average if the respondent provides a range)

ITEM	UNIT	Fruit/Vegetable Name			
		1	2	3	4
Acre of land for the vegetable	Mu				
Yield per acre	0.5kg/Mu				
Average Selling	Yuan/0.5kg				
Total cost for acre	Yuan/Mu				
Net profit for acre	Yuan/Mu				

The following questions in Part II are retrospective questions. Please let the respondent recollects these information as much as possible.

Q9. Have you ever been attached by any severe disaster that caused your yield reduce more than 50% within the last ten years (from 2007-2016)? If yes, how many times? If no, skip Q8.

Q10. What was the loss of ratio when each disaster occurred in last ten years? (Check multiple boxes if necessary)

Five out of ten. □ □ □ □ □

Six out of ten. □ □ □ □ □

Seven of out of ten □ □ □ □ □

Eight out of ten. ☐ ☐ ☐ ☐ ☐

Nine out of ten ☐ ☐ ☐ ☐ ☐

Total loss. ☐ ☐ ☐ ☐ ☐

Part III: Risk Perception and Insurance

Q1. Do you know about vegetable insurance?

A. Yes. If yes, go to Q2
B. No. ***If no, the enumerator should explain what is vegetable insurance, including the current premium, subsidy level and coverage level to the respondent, and then go to Q5.***

Q2. Do you currently hold vegetable insurance contract?

A. Yes. If yes, go to Q3.
B. No. If no, go to Q6.

Q3. Do you know how much government subsidizes premium for each unit? If yes,

please state how much. (Go to next question)

A. Yes. ***If yes, please let the respondent say the subsidy ratio. Only the correct ratio counts "yes".***
B. No.

Q4. How many years have you held vegetable insurance contract for?

☐ 2017 ☐ 2016 ☐ 2015 ☐ 2014 ☐ 2013 ☐ 2012

☐ 2011 ☐ 2010 ☐ 2009 ☐ 2008

Q5. Would you buy the existing insurance contract for the fruit/vegetable you are

currently growing?

A. Yes. ***If yes, go to Q7.***
B. No. ***If no, go to Q6.***

Q6. Are you willing to buy the insurance?

A. Yes
B. No

Q7. Reasons you do not purchase insurance include (Check all options apply. ***Go to Q7***)

A. The probability of disaster is low, making vegetable insurance unnecessary.
B. The premium of vegetable insurance is high, making it unaffordable.
C. The indemnity is low, making no difference once the disaster occurs.
D. The income from growing fruit/vegetable is not one of the major sources of income.
E. Be concerned that there is possibility that contract holder cannot to obtain indemnity when the disaster occurs.
F. Others. ***(Please be specific)***

Q7. What is the probability of disaster (including all the weather-related disaster) that would cause severe loss (reduce over 30% yield) in you opinion?

A. Less than 1%
B. 1%~5%
C. 5.1%~10%
D. 10.1%~20%.
E. 20.1%~30%
F. 31%~40%.
G. 41%~50%.
H. 50.1%~60%.
I. Over 61%.

Q9. Would you buy vegetable insurance contracts with the following indemnity and corresponding premium? (Explain to the respondent if necessary)

If the respondent's income comes from growing vegetable in the field, use Table 1. If the respondent's income comes from growing vegetable in the greenhouse, use Table 2.

Table 1.

Maximum indemnity (Yuan)	Premium (Yuan)	Buy or not
500	10	☐ Yes ☐ No
1000	20	☐ Yes ☐ No
1500	30	☐ Yes ☐ No
2000	40	☐ Yes ☐ No
3000	60	☐ Yes ☐ No
4000	80	☐ Yes ☐ No
5000	100	☐ Yes ☐ No
6000	120	☐ Yes ☐ No
7000	140	☐ Yes ☐ No
8000	160	☐ Yes ☐ No

Note: The current maximum indemnity is 1000 Yuan and premium rate is 20 Yuan. The premium rate here is 10%. Government subsidizes 80% of the premium.

Table 2.

Maximum indemnity (Yuan)	Premium rate	Premium (Yuan)	Buy or not
Frame 10000	12‰	88	☐ Yes ☐ No
Film 1200	20%		
Crop 2000	4%		
Frame 10000	12‰	96	☐ Yes ☐ No
Film 1200	20%		
Crop 3000	4%		
Frame 10000	12‰	104	☐ Yes ☐ No
Film 1200	20%		
Crop 4000	4%		
Frame 10000	12‰	120	☐ Yes ☐ No
Film 1200	20%		
Crop 5000	4%		
Frame 10000	12‰	112	☐ Yes ☐ No
Film 1200	20%		
Crop 5000	4%		
Frame 10000	12‰	120	☐ Yes ☐ No
Film 1200	20%		
Crop 6000	4%		
Frame 10000	12‰	128	☐ Yes ☐ No
Film 1200	20%		
Crop 7000	4%		
Frame 10000	12‰	136	☐ Yes ☐ No
Film 1200	20%		
Crop 8000	4%		
Frame 10000	12‰	144	☐ Yes ☐ No
Film 1200	20%		
Crop 9000	4%		
Frame 10000	12‰	152	☐ Yes ☐ No
Film 1200	20%		
Crop 10000	4%		

Note: The current maximum indemnity is14200 yuan and premium is 96 yuan (The second insurance). The premium rate here is 10%. Government subsidizes 80% of the premium.

----------------The End, please go to experiment section ---------------------

Appendix III - Tables Presented In WTP Experiment and TCN Experiment

WTP Experiment

Tables Presented to Group A

Trial game without monetary payment

Please image you are going to grow okra, which can bring you the revenue per mu as follows in 20 years (see Table 1). There are 3 different insurance contracts for you. You will face 3 tables and answer 3 questions.

Please read through the Table 1 and make your choice for Question 1.

Table 1

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	18063	18063
2	16501	16501
3	3552	5126
4	23773	23773
5	11804	11804
6	26216	26216
7	2762	5126
8	21519	21519
9	26300	26300
10	11280	11280
11	5631	5631
12	7284	7284
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	12966
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 1. I would like to pay________ **at most** to switch from Col I to Col II:

A．0 B. 39 C. 79 D. 118 E. 158 F. 197 G. 236 H. 276 I. 315 J. 35

Please read through the Table 2 and make your choice for Question 2.

Table 2

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	18063	18063
2	16501	16501
3	3552	10251
4	23773	23773
5	11804	11804
6	26216	26216
7	2762	10251
8	21519	21519
9	26300	26300
10	11280	11280
11	5631	10251
12	7284	10251
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	12966
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 2. I would like to pay________ **at most** to switch from Col I to Col II:
A．0 B. 218 C. 436 D. 654 D. 871 E. 1089 F. 1307 G. 1525 H. 1742 I. 1960

Please read through the Table 3 and make your choice for Question 3.

Table 3

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	18063	18063
2	16501	16501
3	3552	15377
4	23773	23773
5	11804	15377
6	26216	26216
7	2762	15377
8	21519	21519
9	26300	26300
10	11280	15377
11	5631	15377
12	7284	15377
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	15377
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 3. I would like to pay________ **at most** to switch from Col I to Col II:

A．0 B. 524 C. 1047 D. 1571 D.2094 E. 2618 F. 3142 G. 3665 H. 4189 I. 4712

Formal game with monetary payment

Table 1. Insurance Contract #1.

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	28629	28629
2	4802	5504
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	5504
7	19853	19853
8	13342	13342
9	24113	24113
10	10578	10578
11	20230	20230
12	18490	18490
13	5038	5504
14	24281	24281
15	24400	24400
16	14128	14128
17	14577	14577
18	23375	23375
19	13084	13084
20	36318	36318

I would like to pay________ at most to switch from Col I to Col II:

A． 0 B. 30 C. 60 D. 88 E. 118 F. 147 G. 176 H. 205 I. 235 J. 265

Table 2. Insurance Contract #2.

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	28629	28629
2	4802	11007
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	11007
7	19853	19853
8	13342	13342
9	24113	24113
10	10578	11007
11	20230	20230
12	18490	18490
13	5038	11007
14	24281	24281
15	24400	24400
16	14128	14128
17	14577	14577
18	23375	23375
19	13084	13084
20	36318	36318

Note: Col I is exactly same as in Table 1.

I would like to pay________ at most to switch from Col I to Col II:

A． 0 B. 199 C. 398 D. 596 E. 795 F. 994 G. 1192 H. 1390 I.1590 J. 1789

Table 3. Insurance Contract #3.

No.	Col I Revenue without insurance (yuan)	Col II Revenue with insurance (yuan)
1	28629	28629
2	4802	16511
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	16511
7	19853	19853
8	13342	16511
9	24113	24113
10	10578	16511
11	20230	20230
12	18490	18490
13	5038	16511
14	24281	24281
15	24400	24400
16	14128	16511
17	14577	16511
18	23375	23375
19	13084	16511
20	36318	36318

Note: Col I is exactly same as in Tables 1 and 2.

I would like to pay________ at most to switch from Col I to Col II:

A． 0 B. 528 C. 1056 D. 1584 E. 2112 F. 2640 G. 3168 H. 3696 I.4224 J. 4752

Tables Presented to Group B

<u>Trial game without monetary payment</u>

You will face 3 tables and answer 3 questions.

Please read through the Table 1 and make your choice for Question 1.

Table 1.

No.	Col I	Col II
1	18063	18063
2	16501	16501
3	3552	5126
4	23773	23773
5	11804	11804
6	26216	26216
7	2762	5126
8	21519	21519
9	26300	26300
10	11280	11280
11	5631	5631
12	7284	7284
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	12966
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 1. I would like to pay________ **at most** to switch from Col I to Col II:

A．0 B. 39 C. 79 D. 118 E. 158 F. 197 G. 236 H. 276 I. 315 J. 355

Please read through the Table 2 and make your choice for Question 2.

Table 2.

No.	Col I	Col II
1	18063	18063
2	16501	16501
3	3552	10251
4	23773	23773
5	11804	11804
6	26216	26216
7	2762	10251
8	21519	21519
9	26300	26300
10	11280	11280
11	5631	10251
12	7284	10251
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	12966
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 2. I would like to pay________ **at most** to switch from Col I to Col II:

A． 0 B. 218 C. 436 D. 654 E. 871 F. 1089 G. 1307 H. 1525 I. 1742 J. 1960

Please read through the Table 3 and make your choice for Question 3.

Table 3.

No.	Col I	Col II
1	18063	18063
2	16501	16501
3	3552	15377
4	23773	23773
5	11804	15377
6	26216	26216
7	2762	15377
8	21519	21519
9	26300	26300
10	11280	15377
11	5631	15377
12	7284	15377
13	26740	26740
14	23777	23777
15	27152	27152
16	12966	15377
17	19273	19273
18	21186	21186
19	17085	17085
20	18846	18846

Question 3. I would like to pay________ **at most** to switch from Col I to Col II:

A．0 B. 524 C. 1047 D. 1571 E.2094 F. 2618 G. 3142 H. 3665 I. 4189 J. 4712

Formal game with money payment

Decision #1

Table 1.

No.	Col I	Col II
1	28629	28629
2	4802	5504
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	5504
7	19853	19853
8	13342	13342
9	24113	24113
10	10578	10578
11	20230	20230
12	18490	18490
13	5038	5504
14	24281	24281
15	24400	24400
16	14128	14128
17	14577	14577
18	23375	23375
19	13084	13084
20	36318	36318

I would like to pay________ **at most** to switch from Col I to Col II:

A． 0 B. 30 C. 60 D. 88 E. 118 F. 147 G. 176 H. 205 I. 235 J. 265

Decision #2

Table 2.

No.	Col I	Col II
1	28629	28629
2	4802	11007
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	11007
7	19853	19853
8	13342	13342
9	24113	24113
10	10578	11007
11	20230	20230
12	18490	18490
13	5038	11007
14	24281	24281
15	24400	24400
16	14128	14128
17	14577	14577
18	23375	23375
19	13084	13084
20	36318	36318

Note: Col I is exactly same with that in Table 1

I would like to pay________ **at most** to switch from Col I to Col II:

A． 0 B. 199 C. 398 D. 596 E. 795 F. 994 G. 1192 H. 1390 I.1590 J. 1789

Decision #3

Table 3.

No.	Col I	Col II
1	28629	28629
2	4802	16511
3	23860	23860
4	26012	26012
5	18073	18073
6	3731	16511
7	19853	19853
8	13342	16511
9	24113	24113
10	10578	16511
11	20230	20230
12	18490	18490
13	5038	16511
14	24281	24281
15	24400	24400
16	14128	16511
17	14577	16511
18	23375	23375
19	13084	16511
20	36318	36318

Note: Col I is exactly same with that in Table 1

I would like to pay________ **at most** to switch from Col I to Col II:

A． 0 B. 528 C. 1056 D. 1584 E. 2112 F. 2640 G. 3168 H. 3696 I.4224 J. 4752

TCN Experiment

Table 4

Row	No.	Lottery A	Lottery B
1	1	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 34 Yuan and 90% winning 2 Yuan
2	2	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 38 Yuan and 90% winning 2 Yuan
3	3	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 42 Yuan and 90% winning 2 Yuan
4	4	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 47 Yuan and 90% winning 2 Yuan
5	5	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 53 Yuan and 90% winning 2 Yuan
6	6	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 63 Yuan and 90% winning 2 Yuan
7	7	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 75 Yuan and 90% winning 2 Yuan
8	8	30% winning 15 Yuan and 70% wining 5 Yuan	10% winning 93 Yuan and 90% winning 2 Yuan
9	9	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 110 Yuan and 90% winning 2 Yuan
10	10	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 150 Yuan and 90% winning 2 Yuan
11	11	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 200 Yuan and 90% winning 2
12	12	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 400 Yuan and 90% winning 2 Yuan
13	13	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 400 Yuan and 90% winning 2 Yuan
14	14	30% winning 15 Yuan and 70% winning 5 Yuan	10% winning 500 Yuan and 90% winning 2 Yuan

I choose Lottery A for Line 1 to _____.

I choose Lottery B for Line _____ to 14.

Table 5

Row	No.	Lottery A	Lottery B
15	1	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 25 Yuan and 30% winning 2 Yuan
16	2	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 27 Yuan and 30% winning 2 Yuan
17	3	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 29 Yuan and 30% winning 2 Yuan
18	4	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 31 Yuan and 30% winning 2 Yuan
19	5	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 33 Yuan and 30% winning 2 Yuan
20	6	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 35 Yuan and 30% winning 2 Yuan
21	7	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 39 Yuan and 30% winning 2 Yuan
22	8	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 41 Yuan and 30% winning 2 Yuan
23	9	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 45 Yuan and 30% winning 2 Yuan
24	10	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 50 Yuan and 30% winning 2 Yuan
25	11	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 55 Yuan and 30% winning 2 Yuan
26	12	90% winning 20 Yuan and 10% winning 15 Yuan	70% winning 65 Yuan and 30% winning 2 Yuan

I choose Lottery A for Line 1 to _____.

I choose Lottery B for Line _____ to 12.

Table 6

Row	No.	Lottery A	Lottery B
27	1	50% winning 15 Yuan and 50% losing 1 Yuan	50% winning 18 Yuan and 50% losing 5 Yuan
28	2	50% winning 10 Yuan and 50% losing 1 Yuan	50% winning 18 Yuan and 50% losing 5 Yuan
29	3	50% winning 5 Yuan and 50% losing 1 Yuan	50% winning 18 Yuan and 50% losing 5 Yuan
30	4	50% winning 4 Yuan and 50% losing 2 Yuan	50% winning 18 Yuan and 50% losing 5 Yuan
31	5	50% winning 4 Yuan and 50% losing 2 Yuan	50% winning 18 Yuan and 50% losing 4 Yuan
32	6	50% winning 3 Yuan and 50% losing 2 Yuan	50% winning 18 Yuan and 50% losing 4 Yuan

I choose Lottery A for Line 1 to _____.

I choose Lottery B for Line _____ to 6.