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Farmers' Risk Preferences and Agricultural Weather Index Insurance Uptake in Rural China

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Abstract The purpose of this study is to investigate the effect of farmers' risk preferences on their decisions to purchase the agricultural weather index insurance based on the evidence from a household survey and field experiments conducted in Yongqiao District, Suzhou City of Anhui Province in China. Our empirical results show that farmers' risk aversion significantly increases the probability of their decision to buy weather index-based crop insurance. Other factors that significantly influence weather index insurance participation decisions include farmers' subjective beliefs on the probability of crop losses, farming experience, education level, farm size, and their household income. The empirical results of this study can provide helpful insights for policymakers and local insurers to further improve farmers' participation in weather index-based crop insurance.

Keywords China · Farmers' risk aversion · Risk preference · Weather index insurance

1 Introduction

Climate-related catastrophic disasters may increase in frequency and severity in the future due to climate change (IPCC 2007). China is highly exposed to natural hazards and disasters and the potential impact of climate change (Sun et al. 2016). In the past decades, natural hazards and disasters have affected about a quarter to one-third of the arable land in China (Liu et al. 2010). Agricultural insurance policy is considered one of the most important and useful risk mitigation strategies that can transfer the risk of agricultural production and reduce farmers' economic losses (Thomas et al. 2007; Xiu et al. 2012; Panda et al. 2013). The importance of developing an agricultural insurance policy has always been highlighted by the Chinese government in the annual government No. 1 Document since 2004 (Liu et al. 2010). Particularly in 2012, the Chinese central government made an explicit proposal to expand the types of product and coverage of agricultural insurance in rural China (Ye et al. 2016).

However, conventional agricultural insurance with a single rate has some well-known problems, including adverse selection (Quiggin et al. 1993; Just et al. 1999; Makki and Somwaru 2001), moral hazard (Horowitz and Lichtenberg 1993; Smith and Goodwin 1996), and systemic risk (Miranda and Glauber 1997; Miranda and Farrin 2012). Given these problems associated with conventional agricultural insurance, in the past two decades a growing number of national governments, academic researchers, and international nongovernmental organizations have exhibited great interest in a new form of agricultural insurance known as weather index insurance, which is based on recorded meteorological data that are highly associated with crop losses (Barnett and Mahul 2007; Bryla and Syroka 2007; Chantarat et al. 2007; Miranda and Farrin 2012; Cao et al. 2013). In the contexts involving rural smallholder farmers, weather index products have distinct advantages over conventional crop insurance (Patt et al. 2009; Liu et al. 2010) and are increasingly preferred by local farmers and insurers (Collier et al. 2009; Akter et al. 2016). As the weather index insurance is a relatively new product in China, it has not been widely implemented. A better understanding of factors influencing farmers'

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decisions on purchasing weather index insurance is of great importance to help policymakers and insurers design better insurance policies (Patt et al. 2009; Botzen and van den Bergh 2012).

The number of studies that looked into the factors that might influence farmers' decisions on purchasing agricultural insurance are growing (Sherrick et al. 2004; Petrolia et al. 2013; Simon and Fiorentino 2014; Ye et al. 2016). Because of different climatic, economic, political, and institutional conditions, farmers' participation decisions on agricultural insurance and their determinants may be different in different countries and regions (Hisali et al. 2011). Therefore, more location- or country-specific empirical studies on the factors that determine farmers' agricultural insurance uptake decisions are needed (Uy et al. 2011). Moreover, weather index insurance based on the observed value of a specified meteorological or weather "index" is different from conventional agricultural insurance, so the factors that determine farmers' uptake decisions could be different as well.

The standard theoretical model of behavior under risk assumes that farmers' risk preferences play an important role in their decisions under uncertainty (Just et al. 1983; Lusk and Coble 2005; Liu and Huang 2013; Qiu et al. 2014). However, studies that explore the potential impact of farmers' risk preferences on the decisions to purchase weather index insurance have been few. The present study contributes to this literature by examining whether Chinese farmers' weather index insurance participation decisions are correlated with their risk preferences. Individual risk preferences have been measured using economic experiments that often use students or small groups of people as convenience samples (Fox and Clemen 2005; Bleichrodt et al. 2010). Different from the above literature, this study examines farmers' preferences toward risk by means of an experimental approach using field level data. The findings of this study can add to the literature on weather index insurance demand, particularly as it relates to the smallholder farmers in developing countries.

The following section describes the study area, research design, and data collection. The empirical results are reported and discussed in the third section. The final section summarizes the findings of the study.

2 Methods and Data Collection

This study developed a modified multiple price list design to measure farmers' risk preferences and conducted a face-to-face household survey of 200 household heads in November 2013.

2.1 Study Area and the Weather Index Insurance

This study selected Yongqiao District in Suzhou City of Anhui Province as the study area. Yongqiao, located in the north of Anhui Province between latitudes 33°20′N and 34°02′N and longitudes 116°59′E and 117°20′E, is the largest county-level district in China. It covers a total area of 2868 km^2 with a population of 1.8 million. The annual GDP per capita was about RMB 16,987 Yuan (USD 2831) in 2014. The district receives an annual average rainfall of 900 mm. The average annual temperature is about 14 °C. The district is a drought-prone area (Xu et al. 2013).

The study area choice was made because Yongqiao was one of the regions where wheat weather index insurance was first introduced (in 2009) by Guoyuan Agricultural Insurance Company. This insurance provides multi-peril coverage for wheat yield loss due to drought (less rainfall and high temperature). Different from conventional crop insurance, the payment of this weather index insurance is triggered and measured by anomalies in the meteorological data rather than the damage to crops.

The weather indices were designed based on the 1993–2009 daily meteorological observation data combined with the main agrometeorological disasters for winter wheat of the region during the growing season and the relationship with historical yield loss (Yang et al. 2013). Table 1 shows the trigger values of insurance payment. The premium was RMB 150 Yuan (USD 25) per hectare. Farmers paid 20% of the premium cost and the rest was subsidized by a combination of local, provincial, and central government funds.

2.2 Survey and Experiment Design

Four focus group discussions and three pretests were conducted to develop and refine the survey instruments and experiment scripts before conducting the full survey in 2013. Farmers were offered RMB 50 Yuan (approximately USD 8) as compensation for participating in our research session.

The questionnaire contained questions about knowledge and perceptions of the risks caused by change in the local climate, experiences of crop losses caused by adverse weather conditions, respondents' subjective beliefs about the probability of their crops incurring losses during the upcoming growing season due to weather events, and knowledge and experience of the weather index insurance. Respondents were asked whether they had heard about the weather index insurance and their information source. They were further asked whether they had purchased such insurance, as well as the reasons for their being insured or not. Each participant was also asked to provide their farming background, farm characteristics, and socioeco-

Table 1 Trigger values of weather index insurance payment

Indices	Time period	Trigger value
Drought index I	From 15 May to 31 August	Cumulative rainfall <230 mm
Drought index II	From 1 September to 15 October	Cumulative rainfall <15 mm
High-temperature index	From 30 July to 15 August	Highest daily temperature >35 °C for more than 5 days and the cumulative number of degrees over 35 > 8 °C

nomic/demographic and household information. The risk-preference elicitation experiment was conducted right after the household survey.

For the experiment, this study used a modified multiple price list (MPL) design based on the widely used Holt–Laury type measure to elicit farmers' risk preferences (Holt and Laury 2002; Brick et al. 2012). The advantage of this MPL design is that it can be explained and implemented with relative ease. This design can also encourage truthful revelation of risk preferences (Andersen et al. 2006).

In our experiment, subjects were asked to make a series of eight choices between two options, A and B (Table 2). Throughout the eight tasks, the payoff associated with option A declines systematically, while the expected payoff for option B remains unchanged. The expected payoffs of option A and B, which were not presented to subjects, are reported in the fourth and fifth columns of Table 2. To ensure incentive compatibility, each subject was told that he/she would be paid by cash based on one of the eight decisions that he/she made in the experiment.

In the expected utility theory context, we can elicit a parameter r describing risk attitude based on the point at which a subject switches from option A to option B, which can be used to determine the range of the subject's risk aversion parameter value. Following Holt and Laury's procedure (Holt and Laury 2002), we assume a utility function of constant relative risk aversion to determine the

upper and lower bounds of this parameter. The constant relative risk aversion utility function specification for individual i is as follows (Anderson and Mellor 2008):

$$u_i(x) = \frac{x^{1-r}}{1-r},$$

where x is the payoff in the option, and r is the coefficient of relative risk aversion (CRRA). We can define subjects' risk preferences based on the value of CRRA, with $r < 0$ denoting risk loving, $r = 0$ denoting risk neutral, and $r > 0$ indicating risk aversion.

2.3 Data Collection

The household surveys and risk experiments were conducted in two villages (Danan and Sanli) in Dadian Town of Yongqiao District. In 2013, the total population was 4638 in Danan village and 4337 in Sanli village. The total area of cropland was around 834 ha and 739 ha in Danan and Sanli, respectively. Wheat and soybeans are the principal crops in the two villages. These two villages were purposively selected as they were the only two villages where the wheat weather index insurance was piloted. Within each administrative village, households were randomly selected from rosters by village leaders. The heads of the selected households were invited to participate in our survey and experiment. If the household head was not

Table 2 The risk experiment design

Task	Option A (Yuan)	Option B (Yuan)	EV^A (Yuan)	EV^B (Yuan)	CRRA interval[†]
1	20	20 if heads; 0 if tails	20	10	$-\infty, -1.4$
2	15	20 if heads; 0 if tails	15	10	$-1.4, -0.4$
3	12	20 if heads; 0 if tails	12	10	$-0.4, 0$
4	10	20 if heads; 0 if tails	10	10	$0, 0.2$
5	8	20 if heads; 0 if tails	8	10	$0.2, 0.4$
6	6	20 if heads; 0 if tails	6	10	$0.4, 0.6$
7	4	20 if heads; 0 if tails	4	10	$0.6, 0.7$
8	2	20 if heads; 0 if tails	2	10	$0.7, \infty$

[†] The coefficient of relative risk aversion (CRRA) interval if subjects switch to Option B (not shown to subjects)

available, the family member who did the most farm work was invited. The household survey method was an individual face-to-face interview.

In November 2013, we conducted the final survey and the risk experiment. In total, 220 household heads were invited and 200 were actually surveyed and participated in the experiment.

3 Empirical Results and Discussion

In this section, we present the main findings and some discussions. The four main parts are: (1) respondents' key socioeconomic characteristics and demographic profile; (2) respondents' subjective risk beliefs about damages caused by drought and high temperature; (3) respondents' awareness and attitudes about the weather index insurance; and (4) the linkage between farmers' risk preferences and their decisions on purchasing the weather index insurance.

3.1 Respondents' Demographic Profile

The respondents' basic socioeconomic characteristics and demographic profile are reported in Table 3. By comparing with the data from the Anhui Statistical Yearbook 2014 (recording the data of 2013), the sample's representativeness was verified. Approximately 42% of respondents were male, while the provincial share of male was 51%. The reason may lie in the absence of many male family heads, who left the village to work in big cities. The representative respondent in our sample was about 41 years old with almost 20-year farming experience. The sample's mean education level was about senior high school, and the average household size was close to five persons. The average farm size was 0.96 ha, and only 25% of the samples had potential access to credit. They borrowed loans from the bank in 2012. The average monthly household

income (USD 584) was close to the provincial average for rural population, which was approximately USD 602.

3.2 Respondents' Subjective Risk Beliefs

One question asked of the respondents was to estimate the annual percentage of crop losses due to bad weather (such as drought, high temperature, and heavy rain) in the last 5 years. The estimation result was 34%, comparable with China's average crop losses due to natural hazards and disasters (Balzer and Hess 2009). Almost all respondents (96%) reported that extreme high temperatures and drought caused reduction of their crop yields in 2012. Of the respondents, 97% thought that their crop yields would be affected by change in the local climate in the future. Respondents' subjective beliefs of the probability of crop losses due to weather events in the coming growing season was 29%, lower than the probability that respondents estimated on their actual crop losses.

3.3 Respondents' Attitudes toward Weather Index Insurance

Respondents were asked about their awareness of the weather index insurance. Our results show that about 70% of the respondents have heard about this insurance product. Among those who have heard about the insurance, they were further asked about their information source. In terms of the entire sample, the majority (118 respondents) said that they learned about this weather index-based insurance from their village leaders. Other information sources included insurance companies (18%) and social networks such as friends and relatives (15%).

In total, 53% of the respondents purchased and were covered by the weather index insurance, while the other 47% remained uncovered. Respondents' reasons for being covered and not being covered are shown in Tables 4 and

Table 3 Socioeconomic characteristics of the respondents

Variable	Description	Mean	SD	Provincial average
Gender	Male = 1, otherwise = 0	0.42	0.49	0.51
Age	Age of the respondents	40.81	12.53	–
Farmyears	Years engaged in farming activities	19.27	12.61	–
Education	Educational level (1 = elementary and below, 2 = junior high school, 3 = senior high school, 4 = college, 5 = university and above)	2.97	0.79	–
Hhsize	Household size	4.81	1.30	4
Landowned	Farm size (ha)	0.96	0.67	–
Credit	Access to credit (yes = 1; no = 0)	0.25	0.43	–
Hhincome	Household income (USD/month)	584	411	602

Table 4 Reasons for being covered

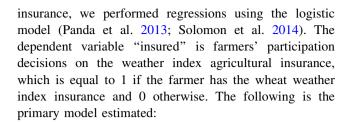| Reasons	Ratio (%)
The insurance premium is appropriate	12.26
The probability of future climatic risk occurring is high	18.87
This program is supported and implemented by the government	18.87
The insurance program was subsidized by the government	29.25
Change in the local climate has caused damage to our crops	18.87
Other reasons	1.89

Table 5 Reasons for not being covered

Reasons	Ratio (%)
The price is too high	20.59
I don't have enough money	23.53
Probably the insurance company would not compensate in case of damage	17.65
The administrative procedures are complex	8.82
The insurance policy is difficult for me to understand	14.71
The insurance information is not enough	8.82
Other reasons	5.88

5, respectively. The most important reason for people to buy this insurance was that the program was subsidized by the government. The other three important reasons included the high probability of future climatic risk, the program was supported and implemented by the government, and change in the local climate had caused damage to their crops. The most important reason for not participating in the insurance program was that respondents' budgets were not sufficient for a purchase of this insurance product. While 20.59% said the price of this insurance was too high, 17.65% did not believe the insurance company would compensate them in case of damage. To improve farmers' participation in the insurance program, it seems that there is a need for local insurers to improve their services and build trust from farmers. Among the nonpurchasers, 14.71% thought the insurance was too complicated to understand. About 8.82% said that the information on the insurance policy was not enough. Thus, detailed and understandable information on the trigger values of abnormal rainfall and temperature and the compensation schemes of the insurance policy should be clearly explained to farmers to promote insurance uptake.

3.4 Farmers' Risk Preferences, Risk Beliefs, and Insurance Uptake

To identify the linkage between farmers' risk preferences and their decisions on purchasing the wheat weather index

insurance, we performed regressions using the logistic model (Panda et al. 2013; Solomon et al. 2014). The dependent variable "insured" is farmers' participation decisions on the weather index agricultural insurance, which is equal to 1 if the farmer has the wheat weather index insurance and 0 otherwise. The following is the primary model estimated:

$$y_i = \beta_0 + \beta_1 Risk_i + \beta X_i + \varepsilon_i$$

where the subscript i indicates an individual, y_i is the binary dependent variable, $Risk_i$ is the CRRA of the individual i, X_i is a vector of socioeconomic factors and perceptional variables, including the respondent's education level, farm size, household monthly income, farming experience, risk preference, and subjective risk belief of future crop loss. ε is the error term assumed to be normally distributed.

We use the CRRA to measure farmers' risk aversion. As shown in Table 1, the lottery choices provide the range of an individual's CRRA coefficient. In our analysis, we use the midpoint of the CRRA interval based on the results of an individual's choices (Lusk and Coble 2005). For example, if an individual chose option A for the first four decision tasks, then he switched to option B for the last four decisions, he will have a CRRA between 0 and 0.2. Such an individual's CRRA would be set at 0.1 value for the remaining analysis.

The mean value of CRRA midpoint is 0.13, suggesting that subjects in our risk experiments were risk averse on average. This result is consistent with the existing literature that most farmers in developing countries are risk averse (Tanaka et al. 2010; Brick et al. 2012; Gong et al. 2016).

One common problem of logistic regression analysis is the multicollinearity among the independent variables (Hosmer and Lemeshow 1989). There are two important indices for multicollinearity diagnosis: tolerance (TOL) and the variance inflation factor (VIF). A value of TOL smaller than 0.2, or a value of VIF greater than 10, is an indicator for multicollinearity (Menard 1995). Before running the regression, we calculated the TOL and VIF indices to explore the potential multicollinearity among independent variables. The diagnosis results are shown in Table 6. It can be seen that the smallest TOL was larger than 0.8 and the largest VIF was less than 2, indicating that there is little multicollinearity between these independent variables.

The regression results are presented in Table 7. Most explanatory variables are as expected and statistically significant at the 10% or lower levels. The results of *Chi square* show that the likelihood ratio statistics are highly significant ($p < 0.001$), suggesting that the explanatory power of the regression model is strong.

Table 6 Multicollinearity diagnosis indices for independent variables

Variables	Description	TOL	VIF
Raversion	Midpoint of CRRA (degree of risk aversion)	0.974	1.026
Lossamount	Crop losses due to bad weather in 2012	0.880	1.136
Futureloss	Subjective risk belief of future crop loss	0.854	1.172
Higheduc	1 = above junior high school; 0 = otherwise	0.951	1.052
Farmyears	Years engaged in farming activities	0.932	1.073
Landowned	Farm size	0.900	1.111
Logincome	Logged value of monthly household income	0.893	1.120
Credit	1 = access to credit; 0 = otherwise	0.951	1.052

Table 7 Parameter estimate of the logistic regression model

Variable	Coef.	SE	P value
Raversion	1.261***	0.43	0.003
Lossamount	1.01	0.83	0.225
Futureloss	0.08***	0.02	0.000
Higheduc	0.84*	0.47	0.073
Farmyears	0.05***	0.02	0.002
Landowned	0.08***	0.03	0.006
Logincome	−0.98*	0.58	0.094
Credit	0.65	0.46	0.151
Constant	−2.08	2.26	0.357
Summary statistics			
Log likelihood	−91.89		
LR chi^2(8)	92.97		
Prob > chi^2	0.000		
Pseudo R^2	0.34		
Observations	200		

*** and * indicate significance levels of 1 and 10%, respectively

It is hypothesized that risk-averse individuals will have a higher probability to be covered by the weather index insurance than those risk-seeking respondents. Our estimation results confirm this hypothesis. The coefficient on farmers' risk aversion is positive and significant (Table 7), showing that risk aversion positively affects the typical farmer's decision on purchasing the weather index insurance. In other words, a risk-averse farmer would be more willing to buy the agricultural weather index insurance. This is consistent with standard economic theory and the existing literature on the linkage between individuals' risk preferences and insurance uptake decisions (Petrolia et al. 2013; Simon and Fiorentino 2014). Thus, it can be anticipated that more risk-averse individuals, such as female farmers, would be more likely to take up the weather index-based insurance.

The regression result also indicates that the farmer's subjective belief in the probability of future crop losses due to weather events has a positive and significant effect on his/her participation decision. This result suggests that farmers who perceive a higher probability of suffering future crop damages are more likely to uptake the insurance. This finding is expected and understandable. If individuals consider that the probability or potential magnitude of loss is low, insurance may appear unattractive, even at subsidized rates (Petrolia et al. 2013). The literature also shows that individuals often underestimate the risk (Camerer and Kunreuther 1989; Chivers and Flores 2002; Kunreuther 2006). Our results may explain why there is still inadequate participation in agricultural insurance markets although the government has highly subsidized the insurance premium.

As expected, the coefficient on farmer's education level is positive and significant. In the literature, an individual's education level has been regarded as a good indicator for his/her ability to understand and use financial insurance tools (Enjorlras and Sentis 2011; Ye et al. 2016). The information on the trigger levels of abnormal rainfall and temperature and compensation schemes of the weather index insurance is conceptually complex. Our survey results also show that many respondents found it difficult to understand the insurance policy. As better-educated farmers can understand the insurance contract better, they are more likely to participate in the insurance program. Thus, promotional efforts to expand the weather index insurance coverage can focus on the ways in which the proposed insurance schemes can be explained and communicated to local farmers.

Our results show that the effect of individuals' farming experiences on the weather index insurance uptake decision is positive. More experienced farmers have a higher probability to purchase the insurance to protect themselves. One possible explanation could be that farmers with more years of farming may have had more bad experiences on crop damages or losses. They are more able to understand the potential risks in farming (Ye et al. 2016).

The coefficient on "Landowned" is positive and highly significant, suggesting that a farmer with more farmland would have a higher probability to buy the weather index

insurance. This result is expected as farmers with more farmland would have more weather-related risks due to abnormal weather and change in the climate, which could lead to a greater demand for the weather index insurance to reduce potential losses.

The results indicate that farmers' household income is negatively and significantly associated with the insurance participation practice. This finding is surprising. It is hypothesized that richer farmers would have a higher demand for the insurance. But the decision on purchasing the crop insurance is affected by many factors (Wang et al. 2016). Instead of buying insurance, richer farmers could recover through other means such as off-farm investments, if their farms are damaged by bad weather conditions.

4 Conclusion

For small-scale farmers in developing countries, weather index insurance is an attractive alternative for climate change adaptation (Akter et al. 2016) and protection of livelihoods. A better understanding of the factors that may influence farmers' decisions on weather index insurance uptake can help insurers and policymakers to make better insurance policies. Farmers' risk preferences play an important role in their farming decisions. However, empirical evidence of the effect of farmers' risk preferences on the adoption of weather index insurance has been rare. In this respect, this study contributes to the literature on the linkage between farmers' risk preferences and their weather index insurance uptake decisions in rural China.

The survey results show that more than half of the respondents purchased the weather index insurance. The main reasons for farmers to participate in the weather index insurance are that the insurance program is supported and subsidized by the government, and the probability of future crop losses due to weather events is high. The important reasons for not being covered by the weather index insurance include farmers' low income, low trust in local insurers, and failure in understanding the complex information of the insurance policy.

The results of the MPL risk experiment show that the typical farmer in our study area is moderately risk averse. The regression analysis results show that risk aversion has a positive effect on farmers' weather index insurance participation decision, which can provide new evidence on the effect of farmers' risk preferences on their decisions to purchase the weather index insurance. Other variables that influence farmers' participation decisions include farmers' subjective beliefs on the probability of crop losses due to weather events, education levels, farming experience, farm size, and household income. The empirical evidence

presented here provides insights that can help policymakers and local insurers to further promote farmers' participation in weather index insurance. In particular, there seems to be a need to find better ways to explain and communicate the information on trigger values and compensation mechanisms of the weather index insurance to relatively less educated farmers.

References

Akter, S., T.J. Krupnik, F. Rossi, and F. Khanam. 2016. The influence of gender and product design on farmers' preferences for weather-indexed crop insurance. *Global Environmental Change* 38: 217–229.

Andersen, S., G.W. Harrison, M.I. Lau, and E.E. Rutström. 2006. Elicitation using multiple price list formats. *Experimental Economics* 9(4): 383–405.

Anderson, L.R., and J.M. Mellor. 2008. Predicting health behaviors with an experimental measure of risk preference. *Journal of Health Economics* 27(5): 1260–1274.

Balzer, N., and U. Hess. 2009. Climate change and weather risk management: evidence from index-based insurance schemes in China and Ethiopia. http://home.wfp.org/stellent/groups/public/documents/newsroom/wfp225958.pdf. Accessed 6 Jun 2013.

Barnett, B.J., and O. Mahul. 2007. Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics* 89(5): 1241–1247.

Bleichrodt, H., A. Cillo, and E. Diecidue. 2010. A quantitative measurement of regret theory. *Management Science* 56(1): 161–175.

Botzen, W.J.W., and J.C.J.M. van den Bergh. 2012. Risk attitudes to low-probability climate change risks: WTP for flood insurance. *Journal of Economic Behavior & Organization* 82(1): 151–166.

Brick, K., M. Visser, and J. Burns. 2012. Risk aversion: Experimental evidence from South African fishing communities. *American Journal of Agricultural Economics* 94(1): 133–152.

Bryla, E., and J. Syroka. 2007. Developing index-based insurance for agriculture in developing countries. Sustainable development innovation briefs. New York: United Nations Department of Economic and Social Affairs.

Camerer, C.F., and H. Kunreuther. 1989. Decision processes for low-probability events: Policy implications. *Journal of Policy Analysis and Management* 8(4): 565–592.

Cao, J., L. Yang, and S. Li. 2013. Design of wheat drought index insurance in Shandong Province. *International Journal of Hybrid Information Technology* 6(4): 95–104.

Chantarat, S., C.B. Barrett, A. Mude, and C. Turvey. 2007. Using weather index insurance to improve drought response for famine prevention. *American Journal of Agricultural Economics* 89(5): 1262–1268.

Chivers, J., and N.E. Flores. 2002. Market failure in information: The national flood insurance program. *Land Economics* 78(4): 515–521.

Collier, B., J. Skees, and B. Barnett. 2009. Weather index insurance and climate change: Opportunities and challenges in lower income countries. *The Geneva Papers on Risk Insurance Issues and Practice* 34(3): 401–424.

Enjorlras, G., and P. Sentis. 2011. Crop insurance policies and purchases in France. *Agricultural Economics* 42(4): 475–486.

Fox, C.R., and R.T. Clemen. 2005. Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. *Management Science* 51(9): 1417–1432.

Gong, Y.Z., K. Baylis, R. Kozak, and G. Bull. 2016. Farmers' risk preferences and pesticide use decisions: Evidence from field experiments in China. *Agricultural Economics* 47(4): 411–421.

Hisali, E., P. Birungi, and F. Buyinza. 2011 Adaptation to climate change in Uganda: Evidence from micro level data. *Global Environmental Change* 21(4): 1245–1261.

Holt, C.A., and S.K. Laury. 2002. Risk aversion and incentive effects. *American Economic Review* 92(5): 1644–1655.

Horowitz, J.K., and E. Lichtenberg. 1993. Insurance, moral hazard, and chemical use in agriculture. *American Journal of Agricultural Economics* 75(4): 926–935.

Hosmer, D.W., and S. Lemeshow. 1989. *Applied regression analysis*. New York: Wiley.

IPCC (Intergovernmental Panel on Climate Change). 2007. Climate change 2007: Synthesis report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC.

Just, R.E., L. Calvin, and J. Quiggin. 1999. Adverse selection in crop insurance: Actuarial and asymmetric information incentives. American Journal of Agricultural Economics 81(4): 834–849.

Just, R.E., D. Zilberman, and E. Hochman. 1983. Estimation of multi-crop production functions. *American Journal of Agricultural Economics* 65(4): 770–780.

Kunreuther, H. 2006. Disaster mitigation and insurance: Learning from Katrina. *Annals of the American Academy of Political and Social Science* 604(1): 208–227.

Liu, B.C., M.S. Li, Y. Guo, and K. Shan. 2010. Analysis of the demand for weather index agricultural insurance on household level in Anhui, China. *Agriculture and Agricultural Science Procedia* 1: 179–186.

Liu, E.M., and J. Huang. 2013. Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics* 103: 202–215.

Lusk, J.L., and K.H. Coble. 2005. Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics* 87(2): 393–405.

Makki, S.S., and A. Somwaru. 2001. Evidence of adverse selection in crop insurance markets. *Journal of Risk and Insurance* 68(4): 685–708.

Menard, S.W. 1995. *Applied logistic regression analysis*. Thousand Oaks, CA: SAGE Publications.

Miranda, M.J., and K. Farrin. 2012. Index insurance for developing countries. *Applied Economic Perspective and Policy* 34(3): 391–427.

Miranda, M.J., and J.W. Glauber. 1997. Systemic risk, reinsurance, and the failure of crop insurance markets. *American Journal of Agricultural Economics* 79(1): 206–215.

Panda, A., U. Sharma, K.N. Ninan, and A. Patt. 2013. Adaptive capacity contributing to improved agricultural productivity at the household level: Empirical findings highlighting the importance of crop insurance. *Global Environmental Change* 23(4): 782–790.

Patt, A., N. Peterson, M. Carter, M. Velez, U. Hess, and P. Suarez. 2009. Making index insurance attractive to farmers. *Mitigation and Adaptation Strategies for Global Change* 14(8): 737–753.

Petrolia, D., C.E. Landary, and H.C. Keith. 2013. Risk preferences, risk perceptions and flood insurance. *Land Economics* 89(2): 227–245.

Qiu, Y., G. Colson, and C. Grebitus. 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. *Ecological Economics* 107: 216–229.

Quiggin, J., G. Karagiannis, and J. Stanton. 1993. Crop insurance and crop production: An empirical study of moral hazard and adverse selection. *Australian Journal of Agricultural Economics* 37(2): 95–113.

Sherrick, B.J., P.J. Barry, P.N. Ellinger, G.D. Schnitkey. 2004. Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics* 86(1): 103–114.

Simon, C., and G.T. Fiorentino. 2014. The impact of risk preference on health insurance and health expenditures in the United States. *Applied Economics Letters* 21(9): 7–9.

Smith, V.H., and B.K. Goodwin. 1996. Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics* 78(2): 428–438.

Solomon, B., J. Agwata, and S. Anyango. 2014. Determinants of adoption choices of climate change adaptation strategies in crop production by small scale farmers in some regions of central Ethiopia. *Journal of Natural Sciences Research* 4(4): 78–92.

Sun, Z., S.F. Jia, Lv Aifeng, and Y. Cao. 2016. Impacts of climate change on growth period and planting boundaries of spring wheat in China under RCP4.5 scenario. *Journal of Resources and Ecology* 7(1): 1–11.

Tanaka, T., C. Camerer, and Q. Nguyen. 2010. Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Review* 100(1): 557–571.

Thomas, D.S.G., C. Twyman, H. Osbahr, and B. Hewitson. 2007. Adaptation to climate change and variability: Farmer responses to intra-seasonal precipitation trends in South Africa. *Climatic Change* 83(3): 301–322.

Uy, N., Y. Takeuchi, and R. Shaw. 2011. Local adaptation for livelihood resilience in Albay, Philippines. *Environmental Hazards* 10(2): 139–153.

Wang, M., T. Ye, and P. Shi. 2016. Factors affecting farmers' crop insurance participation in China. *Canadian Journal of Agricultural Economics* 64(3): 479–492.

Xiu, F.L., F.G. Xiu, and S. Bauer. 2012. Farmers' willingness to pay for cow insurance in Shaanxi Province, China. *Procedia Economics and Finance* 1: 431–440.

Xu, X., Q. Ge, J. Zheng, E. Dai, X. Zhang, S. He, and G. Liu. 2013. Agricultural drought risk analysis based on three main crops in prefecture-level cities in the monsoon region of east China. *Natural Hazards* 66(2): 1257–1272.

Yang, T.M., B.C. Liu, X.B. Sun, D. Li, and S.P. Xun. 2013. Design and application of the weather indices of winter wheat planting insurance in Anhui Province. *Chinese Journal of Agrometeorology* 34(2): 229–235 (in Chinese).

Ye, T., Y. Liu, J. Wang, M. Wang, and P. Shi. 2016. Farmers' crop insurance perception and participation decisions: empirical evidence from Hunan, China. *Journal of Risk Research*. 10.1080/13669877.2015.1118151.