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Exploring farmers' willingness to pay for crop insurance products: A case of weather-based crop insurance in Punjab, India

K S Aditya^{1*}, Avinash Kishore², and Md Tajuddin Khan^{2,3}

¹ICAR-Indian Agricultural Research Institute, New Delhi 110 012

²International Food Policy Research Institute (IFPRI), South Asia Office, New Delhi 110 012

³Oklahoma State University, Stillwater, OK, USA

*Corresponding author: adityaag68@gmail.com

Abstract The Government of India has launched the Pradhan Mantri Fasal Bima Yojana, a crop insurance scheme that subsidizes the premium and promises to settle claims timely, but are farmers willing to pay? We conducted a contingent valuation study in Punjab, a state where agriculture is irrigated and the risk is estimated to be so low that the government has not implemented crop insurance before. The study is based on primary data of 716 wheat farmers. The study found that the farmers are willing to pay INR 297 per acre for crop insurance, less than the premium based on existing rates.

Keywords Crop insurance, willingness to pay (WTP), contingent valuation method (CVM)

JEL Codes G22, O13, Q10, Q14

Climate-led weather extremities exacerbate rural poverty and threaten the livelihood of farmers (Eoloviae and Petroviae 2014; Birthal and Hazrana 2019; Birthal et al. 2019), and their incomes fluctuate due to weather-induced risks. Extreme weather events shift the entire agricultural economy downwards—wages and asset prices decrease—and raise the magnitude of income loss beyond production loss (Hazell et al. 2010). Farmers' incomes fluctuate primarily because of weather-induced risks, and small and marginal farmers, who have a poor resource base and who are dependent on natural resource endowments, are more vulnerable to such income shocks. If not managed properly, risks in agriculture may slow down economic development (Hazell et al. 2010). In this context, adaptations to climate change are inevitable (Falco et al. 2014).

In the face of risk farmers prefer to smoothen income and give up risky enterprises (Gollier 2003; Liu et al. 2013). Small and marginal farmers are more risk-averse and cannot cope without external help (Abebe and Bogale 2014); they may use inputs sub-optimally to maintain their stock of liquid assets in case their crop

fails (Giné et al. 2012; Boyd et al. 2011). To cope with risks, households self-insure, take help from the community and loans from formal and informal sources, or liquidate assets (Singh 2013), but these methods are ineffective and costly when all the farmers in a region face covariate risks (Hazell 1992; Swain 2014). De-risking small and marginal farmers is important to promote investment and the adoption of newer technologies in farming (Akter et al. 2016). Many countries have adopted a disaster payment programme to help farmers overcome the impact of crop failure, but direct payment schemes do not provide risk protection and these are the least desirable in an economic sense as they are ad hoc and do not induce farmers to invest optimally in inputs (Coble and Barnett 2013).

Insurance products work on the principle of the law of large numbers—if many farmers buy insurance and a few suffer yield loss, the loss can be met out of the total premium collected. Crop insurance can stabilize farm incomes (Abebe and Bogale 2014; Liesivaara and Myyra 2014) by sharing the risks on premium

payments. If the farmer loses their crop due to a peril listed in the insurance contract, they are compensated. Crop insurance reduces the government's need to make disaster payments; it also reduces the risk of lending and, in turn, smoothens credit flow to the agriculture sector. In the absence of insurance, farmers may not take loans because they fear losing their collateral; therefore, insurance raises credit demand (Carter et al. 2007). Crop insurance is often regarded as a first step in developing a sound rural development finance institution, but adoption worldwide has been sporadic—cash-constrained farmers find the premium rates too high, awareness is low, and the insurance market is beset with imperfections (O'Donoghue et al. 2009; Santeramo et al. 2016; Aditya et al. 2018). Farmers find fair actuarial premiums costly, and most governments, particularly in low- and middle-income countries (Babcock 2015), subsidize insurance premiums heavily to ensure that more farmers buy insurance; subsidies also improve risk-sharing and, in turn, the efficiency of insurance programmes in the long run (Swain 2014). Making crop insurance schemes scalable and sustainable presents many challenges (Santeramo et al. 2016), one of which is setting a premium that farmers find affordable (Liesivaara and Myyra 2014).

Weather-indexed crop insurance is based on a publicly observable, exogenous variable, and it is more transparent than yield-indexed insurance (Giné et al. 2012). Weather-indexed crop insurance obviates crop-cutting experiments or inspections, saving money and time and enabling early settlement of claims (Abebe and Bogale 2014; Akter et al. 2016). Yield loss is determined using sophisticated simulation models whenever the weather parameter crosses the pre-specified limit during the crop duration. It can de-risk agriculture in the face of climate change (Ali 2013), but it is not fool-proof—it can be implemented only where automatic weather stations are available and only if the farmer's yield is correlated with parameters measured at weather stations. Poor correlation between yield and weather parameters or errors in the simulation may raise 'basis risk'—the insured farmer suffers crop loss but does not receive compensation—and discourage farmers from insuring their crop the following season. Also, because farmers face many farming risks not related to the weather, weather-

indexed crop insurance can protect farmers from only a few risks (Abebe and Bogale 2014).

Recognizing the importance of agriculture insurance, India launched the Comprehensive Crop Insurance Scheme, its first multiple-peril crop insurance scheme, in 1985 (Giné et al. 2012; Swain 2014; GoI 2014). The Comprehensive Crop Insurance Scheme was modified and launched as the National Agriculture Insurance Scheme. This scheme was later modified as the Modified National Agriculture Insurance Scheme, which was in operation till 2016, when the new Pradhan Mantri Fasal Bima Yojana was launched. Individual farmers' yields are not considered for estimating the compensation to be paid in case of yield loss, and farmers' claims depend on the shortfall in yield compared to normal for the region (Mahul and Verma 2010)—these insurance schemes are 'yield-indexed' and these operate on the 'area basis'. In each region crop-cutting experiments are conducted by the agriculture department to determine the actual yield for the year (Veeramani et al. 2005; Nair 2010). If there is a shortfall in yield, all farmers in the region are compensated at the same rate. Farm-level insurance is difficult because there are many small and marginal holdings in India and a paucity of historical farm-level yield data. Area-based insurance also helps in minimizing the 'moral hazard' in insurance (Singh 2013). Moral hazard is a case where the insured farmers puts lesser efforts to prevent the yield loss. India launched a weather-indexed crop insurance programme on a pilot basis in the 2003 kharif season (Mahul and Verma 2010; Kiran and Umesh 2015). In 2007 it launched the Weather Based Crop Insurance Scheme, in which insurance is linked to a pre-specified pattern of weather index used as a proxy for crop loss.

The Pradhan Mantri Fasal Bima Yojana offers weather-based crop insurance at 2% of the sum insured for kharif crops and 1.5% of the sum insured for rabi crops. This premium rate is highly subsidized, but is it attractive enough for the farmer? What would farmers pay to insure an acre of wheat crop contingent upon a hypothetical weather-indexed insurance product? Do farmers' experiences of risk in previous cropping seasons influence their willingness to pay? We try to answer these questions by estimating the farmer's willingness to pay for a weather-based crop insurance programme in the state of Punjab.

Data and Methods

We purposively selected Punjab for this study because irrigation facilities abound in Punjab, and agriculture is mostly irrigated, and the risk is considered to be so low that no government implemented a crop insurance programme. However, climate change has raised the frequency of weather aberrations and the risk of agriculture.

We collected data from a primary survey of wheat growers in 12 districts of Punjab during 2015-16 season. The study uses a stratified sampling frame, randomly selecting 12 districts from Punjab and in the next stage 2-3 blocks from each district. From each block, two villages were chosen for the study and 12 farmers were randomly surveyed from selected villages resulting in a sample size of 716. The final randomization was based on the household listing of the selected villages.

Economists are interested in assigning a monetary value to non-marketed goods and measuring benefits of government policies, including non-use values (Hanemann et al. 1991), and they commonly use methods like hedonic pricing, travel cost method, and the contingent valuation method (Carson et al. 2001; Abebe and Bogale 2014; Subash et al. 2018). The contingent valuation method aims to estimate, contingent upon the hypothetical market situation, the willingness to pay (or accept) for change in the provision of some goods or services (López-Feldman 2013; Qureshi et al. 2013). Contingent valuation can be carried out using several methods—the most commonly used are open-ended questions, bidding game, single-bound or double-bound dichotomous choice question, and choice experiments—and the most robust are discrete choice methods, double-bound or single bound, because they make decision-making easy for the respondent.

In open-ended questions, the respondent is asked directly to state, contingent upon the hypothetical market, what they would pay for a product or service. The open-end question method is criticized because it requires respondents to think too much about the range of utilities and alternatives and arrive at a suitable price. In the discrete choice format, also called the single bound discrete choice contingent valuation method, a pre-decided bid value is offered to the respondent and they are asked whether they would pay the amount

(Yes/No—discrete choice). The discrete choice format is preferred because it closely mimics the real-life scenario of purchase decisions, where the price of the product is listed and one buys it or goes without. But in this method neither the 'yes' nor the 'no' response is bounded; if the responder agrees to pay the bid amount—say, 'X'—we can infer only that his true willingness to pay exceeds X. This limitation can be overcome by asking a follow-up question, and this method, known as the double-bound contingent valuation method, is more robust and less affected by bias (Kanninen 1995). This study follows the double-bound contingent valuation method. As a test, we asked farmers an open-ended follow-up question: what would they pay to insure their crop? The key to the success of the contingent valuation method lies in developing a hypothetical market situation for the product or service in question and in eliciting the willingness to pay contingent upon it (Carson et al. 2001; Hanley et al. 2001; Kiran and Umesh 2012; Tinch et al. 2015).

This study estimates farmers' willingness to pay for weather-indexed crop insurance. Before presenting the bids, the enumerators explained the details of the insurance programme—the mode of implementation, risks covered, payment vehicle, and loss estimation procedure. Parametric weather indices are used as a proxy for yield in this hypothetical weather-indexed insurance programme, and the correlation between changes in weather parameters—compared to normal with the crop yield, based on simulation—is taken as the base for calculating the compensation payable.

Each respondent is offered a random bid amount and asked whether they are willing to insure their crop at that rate; a dichotomous variable captures the response (yes / no). If the farmer responds yes, the enumerators raises the bid by INR 200 when they ask the second dichotomous choice question; if the farmer responds no, the enumerator lowers the bid by INR 200. Depending on the answer, we have information on two bids and yes / no responses, which distinctively improve the accuracy of the estimates of farmers' willingness to pay (Hanemann et al. 1991; Hanemann and Kanninen 2001; Gao et al. 2010), and we can use this information to estimate the willingness to pay econometrically.

Contingent valuation studies may have biases (Birol et al. 2008; Kimenju and De Groot 2008; Abebe and Bogale 2014)—initial bid bias, hypothetical bias,

strategic bias, vehicle bias, and information bias—and the estimation of discrete choice double-bound models may have econometric issues (Kanninen 1995). Some of these biases are minimized if the guidelines and recommendations of the US National Oceanic Atmospheric Administration (NOAA) are followed (Birol et al. 2008; Kimenju and De Groot 2008; Abebe and Bogale 2014). We used the contingent valuation format suggested by the NOAA to design this study, and we used computer software to randomize the bids before being presented to the farmer to minimize the initial bid bias. The hypothetical market description was presented clearly, which included all the possible actors, modes of implementation, and vehicle of payment. This minimizes the information bias and vehicle bias. However, the hypothetical bias is inherent in all the stated preference methods, and the results should be interpreted with caution. To minimize the bias in the econometric estimation of discrete choice models, Kanninen (1995) recommends that the bids at the extreme ends of the distributions should be minimized and those influential observations can be removed in regression. We use both these steps in our study.

Econometric estimation of the willingness to pay

Let t_1 and t_2 be the two bid amounts and the two variables capturing the response be, respectively, Y_{1i} and Y_{2i} . Farmers can respond (Yes, No), (Yes, Yes), (No, Yes), or (Yes, No).

1. (Yes, No): The farmer is ready to pay the initial bid amount ($Y_{1i} = 1$) but they reject the second bid amount ($Y_{2i} = 0$). The probability of this response is

$$\Pr(Y, N) = \Pr(t_1 \leq \text{WTP} < t_2) \quad \dots(1)$$

if the willingness to pay (WTP) depends on a set of explanatory variables, i.e., $\text{WTP}(Z_i, u_i) = Z_i\beta + u_i$, where Z_i is the vector of explanatory variables and β represents corresponding coefficients. Assuming that the error term is normally distributed with 0 mean and standard deviation of σ , we can rewrite Equation 1 as

$$\Pr(Y, N) = \phi\left(\frac{t_2 - Z_i\beta}{\sigma}\right) - \phi\left(\frac{t_1 - Z_i\beta}{\sigma}\right) \quad \dots(2)$$

2. (Yes, Yes): Here, $Y_{1i} = 1$ and $Y_{2i} = 1$ and probability can be written as

$$\Pr(Y, Y) = \Pr(t_1 < \text{WTP} > t_2) \quad \dots(3)$$

Applying Bayes' rule of probability and rearranging,

$$\Pr(Y, Y) = 1 - \phi\left(\frac{t_2 - Z_i\beta}{\sigma}\right) \quad \dots(4)$$

3. (No, Yes): In this case, $Y_{1i} = 0$ and $Y_{2i} = 1$

$$\Pr(N, Y) = \Pr(t_1 > \text{WTP} \leq t_2) \quad \dots(5)$$

$$\Pr(N, Y) = \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_2}{\sigma}\right) - \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_1}{\sigma}\right) \quad \dots(6)$$

4. (No, No): $Y_{1i} = 0$ and $Y_{2i} = 0$

$$\Pr(N, N) = \Pr(t_1 < \text{WTP} < t_2) \quad \dots(7)$$

$$\Pr(N, N) = 1 - \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_1}{\sigma}\right) \quad \dots(8)$$

Equations 2, 4, 6, and 8 can be expressed in likelihood functions as

$$\begin{aligned} \sum_{i=1}^n & \left(d_i^{yn} \ln \left(\phi\left(\frac{t_2 - Z_i\beta}{\sigma}\right) - \phi\left(\frac{t_1 - Z_i\beta}{\sigma}\right) \right) \right. \\ & + d_i^{yy} \ln \left(1 - \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_1}{\sigma}\right) \right) \\ & + d_i^{ny} \ln \left(\phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_2}{\sigma}\right) - \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_1}{\sigma}\right) \right) \\ & \left. + d_i^{nn} \ln \left(1 - \phi\left(Z_i\frac{\beta}{\sigma} - \frac{t_2}{\sigma}\right) \right) \right) \end{aligned}$$

where d_i^{yn} , d_i^{yy} , d_i^{ny} and d_i^{nn} are indicator variables which takes value zero or one depending on the respective response. From the estimates, we can compute the WTP: $\text{WTP on mean} = \beta_0 * \text{Constant} + \sum_{j=1}^k (\text{Mean value}_j * \beta_j)$, where $j = 1 \dots k$ represents the control, variables used in the analysis. (López-Feldman 2013). We use a non-linear combination of the estimates of regression to estimate both the point and confidence intervals. Suitable controls (Table 1) are selected based on the theoretical expectations and literature review. The willingness to pay is estimated based on the mean value of explanatory variables or control variables. From this estimate, it is difficult to quantify the impact of different variables on the willingness to pay, but it is possible to predict $\widehat{\text{WTP}}$ for each respondent by making use of the coefficients of maximum likelihood

Table 1 Description of the control variables used in the analysis

Variable	Unit	Description
Male-headed household	Dummy	Equal to 1 if the household is male-headed, otherwise 0
Age	years	Age of household head
Literate	Dummy	Equal to 1 if household head is literate, otherwise 0
Backward class	Dummy	Equal to 1 if household is Scheduled Class or Scheduled Tribe, otherwise 0
Agriculture primary occupation	Dummy	Equal to 1 if agriculture is the primary occupation of the, otherwise 0
Land	Acres	Total land cultivated by farmer
Farming experience	Years	Farming experience in years
Adopt zero tillage	Dummy	Equal to 1 if zero tillage adopted, otherwise 0
Perception of insurable risks	Dummy	Equal to 1 if the household head perceives insurable risks in farming, 0 otherwise
Experienced risk in last 3 year	Dummy	Equal to 1 if the household has suffered crop loss due insurable risks in the past three years, 0 otherwise
Indebtedness	Dummy	Equal to 1 if the farmer has taken debt, otherwise 0
Extension contact	Dummy	Equal to 1 if the farmer has received technical knowledge from any of the extension agency, otherwise 0
Asset position	Index	Linear unweighted index of agricultural asset ownership dummies (tube well, pump, tiller, tractor, and seed drill)
Banking literacy	Dummy	Equal to 1 if he has a bank account, 0 otherwise
Kisan Credit Card	Dummy	Equal to 1 if he has a Kisan Credit Card, 0 otherwise
Deficit rainfall	Dummy	Dummy = 1 if actual rainfall is deficit by more than 20 per cent of normal for the district
Unseasonal rainfall	Dummy	Equal to 1 if the rainfall during January to April is more than 20% of the normal rainfall for the district

estimation. The determinants of the willingness to pay for insurance were analysed using $\widehat{WTP}$ as dependent variable with a set of explanatory variables in a simple linear regression framework.

Results

We analysed the data from the primary survey (designed in double-bound contingent valuation format) using the 'dbound' Stata package written by López-Feldman (2013). The landholding size of the respondents was found to average 7.47 acres. All categories of farmers—marginal, small, medium, and large—were fairly represented in the sample, most farmers were literate, and about 55% of the farmers reported yield loss in the previous season (Table 2).

In contingent valuation method studies, it is important to consider the distribution of initial bid amounts to overcome the 'initial bid bias'. We priced our eight

initial bids between INR 400 and INR 2,200 to match the premium amount payable for crop insurance at different rates (Table 3). The premium in the current insurance scheme is 1.5% of the sum insured. In Punjab the wheat yield averages 17 quintals per acre and, at the current minimum support price, the maximum insurable sum is about INR 26,010; therefore, if a farmer insures the entire value of their crop their premium will be around INR 400 per acre. We selected bid amounts starting from INR 400 and we randomized the bids using a computer program, and we minimized the bids above INR 1,000 as they were too high for cash-constrained farmers (Table 3). As the price of a good increases, its demand decreases, and as the bid amount increases the probability of a 'no' response is expected to increase; we employ this 'price test', as it is termed in the contingent valuation method literature (Carson et al. 2000), by tabulating the initial bid and the corresponding response (Table 4). The 'no'

Table 2 Summary statistics of respondents

Variable	Unit	Average value
Farmer age	Years	45.45
Farmer experience	Years	26.16
Land owned	Acres	7.47
Backward class	Dummy = 1 if household is Scheduled Caste, Scheduled Tribe, or Other Backward Class	0.17
Marginal farmer	Dummy = 1 if landholding size is less than 2.5 acre, 0 otherwise	0.15
Small farmer	Dummy = 1 if landholding size is ≥ 2.5 acre and < 5 acre, 0 otherwise	0.24
Medium farmer	Dummy = 1 if landholding size is ≥ 0.5 acre and < 10 acre, 0 otherwise	0.30
Large farmer	Dummy = 1 if landholding size is more than 10 acres, 0 otherwise	0.32
Illiterate	Dummy = 1 if the household head is illiterate, 0 otherwise	0.17
Kisan Credit Card	Dummy = 1 if anyone in the household has a Kisan Credit Card, 0 otherwise	0.39
Bank account holder	Dummy = 1 if the household head has a bank account, 0 otherwise	0.90
Asset index	Linear unweighted index of agricultural asset dummies (tube well, pump, tiller, tractor, and seed drill)	3.20
Perception of insurable risks	Dummy = 1 if the household head perceives insurable risks in farming, 0 otherwise	0.54
Experienced risk	Dummy = 1 if he has experienced risk in farming in past three years, 0 otherwise	0.55
Indebtedness	Dummy = 1 if indebted, 0 otherwise	0.62
Extension contact	Dummy = 1 if household has any formal source of extension contact, 0 otherwise	0.64
Cost of pesticide used	Amount spent on pesticide in INR per ha	1245.20
Deficit rainfall	Dummy = 1 if actual rainfall is deficit by more than 20 per cent of normal for the district, 0 otherwise	0.21

Table 3 Distribution of initial bid

Initial bid	Frequency
400	121
600	142
800	108
1000	154
>1000	191
Total	716

responses rose as the bids increased from INR 400 to INR 1,000 and above, in line with the expectation; 59% of the farmers declined the initial bid of INR 400 and 81% declined the bids of INR 800.

We used the maximum likelihood estimation method to estimate the willingness to pay (Table 5). To improve the accuracy of estimation we use as control the variables related to social position, education, extension contact, risk experience in farming, asset position, and

Table 4 Distribution of initial bid and corresponding answers

Answer1 /Bid	400	600	800	1000	>1000	Total
No	69 (57%)	108 (76%)	87 (81%)	143 (93%)	179 (94%)	586
Yes	52 (43%)	34 (24%)	21 (19%)	11 (7%)	12 (6%)	130
Total	121	142	108	154	191	716

Note Percentage figures in parentheses indicate percentage of total

Table 5 Estimated willingness to pay for crop insurance

Variable	Coefficient	P value
Male-headed household	225.48	0.46
Farmer age	−20.44	0.00
Literate	69.56	0.47
Other Backward Class (OBC)	124.81	0.20
Agriculture primary occupation	59.08	0.59
Land owned	10.21	0.03
Farmer experience	16.11	0.00
Adopter of zero tillage	19.20	0.83
Perception of insurable risks	22.33	0.74
Experienced risk	27.99	0.67
Indebtedness	82.93	0.24
Extension contact	111.32	0.16
Asset index	79.99	0.01
Bank account holder	170.78	0.19
Kisan Credit Card	10.34	0.87
Cost of pesticide used	0.14	0.05
Unseasonal rains	−19.24	0.40
Deficit rainfall	207.29	0.02
Adopter of Improved variety	−0.03	1.00
Like farming	23.97	0.79
Constant	−390.02	0.34
Sigma		
Intercept	576.40	0.00
Willingness to pay	297.02	0.00

	Coefficient.	Std. Err.	P Value	[95% Confidence interval]	
Willingness to pay	297.02	46.68	0.00	205.52	388.53

Note Authors' estimates based on field survey

banking literacy. The coefficients of these control variables (presented in the first part of the table) are positive and significant, and these indicate a positive relationship between a 'yes' response, but the magnitude of influence cannot be inferred from the coefficient. Landholdings and the asset index, the two factors that increase the probability of a 'yes' response to the bid, are the two main indicators of the ability to pay for insurance; both have a positive coefficient, in line with the expectation. Deficit rainfall and pesticide usage are also found to positively influence farmers' willingness to participate in insurance (Akter et al. 2016). Older farmers were reluctant to participate in insurance, as indicated by the negative coefficient for

the 'age' variable; the negative relationship between age and demand for crop insurance is well documented (Abebe and Bogale 2014; Liesivaara and Myyra 2014).

The willingness to pay for weather-indexed insurance was estimated at INR 297 per acre, with a confidence interval of INR 205 per acre to INR 388 per acre. The estimate was statistically significant, too. As a robustness check, we asked farmers an open-ended follow-up question: what would they pay for insurance? The mean value of the responses was INR 271 per acre. If the farmer wants to insure 100% of the threshold value of their crop, the premium for existing crop insurance products averages INR 390 per acre (Table 6). The willingness to pay is lower than the premium,

Table 6 Willingness to pay compared with insurance premium for wheat in Punjab

Average yield of wheat (quintal)	Minimum support price (INR per quintal)	Gross value of crop / maximum sum insured	Willingness to pay (INR per acre)	Premium (sum insured = 100% of gross value, INR per acre)	Premium (sum insured = 75% of gross value, INR per acre)	Premium (sum insured = 50% of gross value, INR per acre)
17	1530	26010	297	390.15	292.6125	195.075

but that does not indicate that farming is risk-free. Most studies have failed to establish a causal link between insurance and the extent of risk (He et al. 2018). The estimated willingness to pay can only cover 75% of the value of the crop at existing premium rate of 1.5%. Earlier insurance schemes report that the sum insured was lower than the value of the crop, which is a cause for concern (Damodaran 2016).

Insurance products are based on the principle of large numbers. If more farmers adopt crop insurance, and only a small proportion of them suffer a loss, risk-sharing can work effectively, as the collected premium of those who did not suffer crop loss can be used to compensate those who did face crop loss. This principle works only when many farmers buy insurance and, as insurance coverage increases, insurance schemes become more effective and premium rates can be reduced. The approach of subsidizing insurance premiums to increase the insurance coverage is popular, and the Pradhan Mantri Fasal Bima Yojana scheme follows the same approach. Linking the premium subsidy with the adoption of climate-smart technologies—like zero tillage, laser land levelling, or stress-tolerant crop varieties—could be an interesting approach to increase the area under insurance. Suitably designed insurance products combined with stress-tolerant crop varieties can have the greatest welfare gain (Awondo et al. 2019). Such bundling of insurance products can increase the adoption of crop insurance and climate-smart technologies and make agriculture more resilient.

We use a simple linear regression model to analyse the factors of farmers' willingness to pay (Table 7). The asset index and landholding size have a positive relationship with the willingness to pay for insurance, and wealthy farmers are more willing to pay (Hazell et al. 2010; Ali 2013; Abebe and Bogale 2014; Liesivaara and Myyra 2014). Variables such as indebtedness,

literacy, and bank account were also positive. Insurance is a financial instrument for risk management, and financial literacy significantly affects demand for crop insurance.

To raise participation in crop insurance schemes, it is important to improve farmers' financial literacy (Giné et al. 2012; Ali 2013; Singh 2013). The coefficient for 'experienced risk' and 'pesticide cost' is positive, indicating that farmers who had recently suffered crop loss are more willing to pay than those who had not (Figure 1); Gollier (2003) reports similar results. The willingness to pay increases more sharply with land ownership for farmers who have suffered crop loss; this effect is observed only for small and marginal

Table 7 Factors of individuals' willingness to pay

Willingness to pay	Coefficient	P value
Farmer age	-19.58	0.00
Backward class	136.09	0.00
Literate	63.99	0.00
Land owned	10.77	0.00
land2	-0.02	0.07
Farmer experience	15.79	0.00
Zero tillage adopter	24.67	0.00
Indebtedness	106.51	0.00
Asset index	82.08	0.00
Bank account holder	199.31	0.00
Kisan Credit Card	4.65	0.31
Cost of pesticide	0.15	0.00
Unseasonal rains	-19.37	0.00
Deficit rainfall	198.14	0.00
Experienced risk	26.82	0.00
Adopter of improved variety	-18.30	0.01
Like farming as profession	44.25	0.00

Note Location fixed effects are used and standard errors clustered at region.

Figure 1 Difference in the willingness to pay of farmers who have and have not experienced risk in farming in the previous cropping season

farmers who are more vulnerable to yield loss.

Interestingly, farmers in districts that witnessed unseasonal rainfall—the rainfall from January to April was 20% more than normal—in the previous year were less willing to pay, probably because they expected the government to compensate them. The wheat crop in Punjab suffered heavily due to unseasonal rains during 2014–15, and the state government announced a compensation ranging from INR 2,000 per acre to INR 8,000 per acre depending on extent of damage. Why would a farmer pay for crop insurance ex ante when the government compensates them for free? (Skees 1993). Traditionally, insurance coverage is lower in drought-prone areas (Aditya et al. 2018); disaster payments may be crowding out potential crop insurance. Improved varieties of wheat—like HD 2967, HD 3086, and WH 1105—are resistant to yellow rust, the major disease of wheat, and farmers who grow these varieties perceive the risk of crop loss to be low, and they are less willing to pay for crop insurance than others; investment in risk mitigation strategies may be crowding out the willingness to pay for crop insurance.

Conclusions

Crop insurance will continue to play a vital role in stabilizing farm income and de-risking agriculture, but subsidizing insurance premiums is necessary to improve the efficiency of insurance and for farmers to buy it. This study of weather-based crop insurance in Punjab indicates that farmers are willing to INR 297 per acre at most to insure their crop and that this premium will let farmers insure only 75% of the threshold value of their crop. We find that farmers' willingness to pay is positively influenced by their financial literacy, wealth, and experience of crop loss. Their willingness to pay is negatively influenced by prior investment in technologies that de-risk agriculture, like the adoption of crop varieties that are resistant to biotic and abiotic stresses, which can also be seen as indication that, in the existing design, crop insurance is not the most preferred option of mitigating risk. The government should look beyond credit in bundling insurance products, therefore, and future research on crop insurance should also explore the option of bundling crop insurance with improved / climate-smart agricultural technologies.

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