Risk Preferences and the Pace of Climate Smart Technology Adoption: A Duration Model Approach from India

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Introduction:

Technological innovation has always been associated with economic development. More particularly, advances in agricultural technologies have been considered as a major factor in improving living standards of rural population. Given the much advocated benefits from new agricultural technologies, the delay in adoption of proven technologies has always puzzled economists. An extensive literature has attempted to explain why farmers do not adopt or delay adoption of new technology. Much of this literature cites low level of education (Foster & Rosenzweig, 1995), lack of information and access to credit (Barrett et al., 2004), learning spillover (Munshi, 2004), tenure insecurity, small farm size, and unreliable supply of complementary inputs as the main constraints to technology diffusion.

Apart from the factors mentioned above, there has been a good deal of enquiry on the role of uncertainty about the effectiveness of a new technology as a major constraint to adoption (Feder,1980). As such, in most developing countries, agriculture is always a risky proposition given its dependence on environmental factors that are beyond farmer's control. Further, any new agricultural technology can have a wide distribution of outcomes increasing the associated uncertainty. So, any new agricultural technology is inherently perceived as an uncertain proposition. Consequently, farmers' perceived uncertainty regarding effectiveness of the technology allows individual risk preferences to play a major role in technology adoption (Holden, 2015).

Many experimental studies in developing countries have assessed how risk preferences affect technology adoption (Binswanger, 1980; Byerlee and Polanco, 1986; Shapiro et al., 1992). Binswanger et al. (1980) elicited the risk preferences of a sample of Indian farmers. They used several elicitation techniques, including a gambling game with real money. Their method measured level of farmer's risk aversion, which was used as an explanatory factor in regression for adoption. Their results showed mixed results and were inconclusive about the role of risk aversion on adoption.

Byerlee and Polanco (1986) analyzed farm survey data from Mexico to investigate the reasons for stepwise adoption of component of a technology package. Their results showed that adoption of new innovation was explained primarily by its profitability and riskiness. Shapiro et al. (1992) used a Tobit model to explain the effect of several variables including risk aversion on adoption of double cropping in the USA. They found that adopters on average were more risk averse than non-adopters. However, other factors, like risk perception were more important than their risk preferences in explaining adoption.

Though there has been a series of studies trying to explain the impact of risk on adoption, most of them have relied on less comprehensive experimental designs that did not test for alternate theories like relative importance of Expected Utility Theory (EUT) and Prospect theory (PT) to explain technology adoption. While using EUT one can only test whether risk aversion plays a role in technology adoption, PT allows a comprehensive testing of roles of risk aversion, loss aversion and probability weighted measure in technology adoption decision.

To date, Liu (2013) and Ward & Singh (2015) are the only studies that comprehensively assess the relevance of EUT and PT for adoption of new types of seeds. In a study of adoption of BT cotton seeds in China, Liu (2013) found that more risk averse and loss averse farmers adopt the BT cotton seed later, while farmers who overweighed smaller probabilities adopted the seeds earlier. Ward and Singh (2015), conducted a similar study on adoption of drought tolerant paddy in India and found that risk averse and loss averse farmers are more likely to switch to new rice seeds which outperform other cultivars under moderate and severe drought conditions. Both these studies clearly show how loss aversion and probability weighting measure is an important parameter, along with risk aversion in defining technology adoption.

This paper investigates into the role of individual's risk preferences in adoption behavior of three climate smart technologies promoted in India; Zero Tillage, Laser land Leveler, and Direct Seeded Rice. These technologies have been termed climate smart as they both help in climate change adaptation by reducing risk & increasing productivity and in climate change mitigation by reducing GHG emissions. This would be one of the first papers to examine the role of risk preferences in the adoption of climate smart technologies.

There are several reasons to focus on individual risk preferences while thinking about adoption of these three technologies. One is that risk attitudes have long been recognized by the theoretical model of technology adoption as an important factor. Omission of risk preferences could bias the coefficients of other significant variables that could be correlated with risk preferences such as wealth and education. Second, Individual risk preferences have shown to be defining wealth accumulation and income growth (McInish, Ramaswami, & Srivastava, 1993). However, since risk preferences are not easily assessed through standard household surveys I propose to use the experimental method to ascertain the risk attitudes and use that measure to explain the adoption of technologies by smallholder farmers.

Background on focused technologies and the study area:

This paper analyzes the adoption of three climate smart technologies in rice-wheat cropping systems in India. Rice–wheat (RW) is the most important cropping system for food security in South Asia with 13.5 M ha of land devoted to this farming system, and providing food for more than 400 million people. In India, the rice-wheat cropping system contributes 26% of total cereal production and 60% of total calorie intake (Gupta et al., 2003). The area under the RW system is static and the productivity and sustainability of the system are threatened, because of the inefficiency of current production practices, shortage of resources such as water and labor, and socioeconomic changes. Pressure is increasing on the limited land, water and increasing variability in the climatic factors are increasingly making it more difficult to meet the increasing demand for food of the burgeoning population.

In order to address the dual need of food security and climate change, the Consultative Group for International Agricultural Research (CGIAR) supported research program on Climate Change, Agriculture and Food Security (CCAFS), in partnership with Indian agricultural research centers and other agencies have introduced an array of technologies and practices under the rubric of climate-smart agriculture (CSA) in India. The three technologies considered in the context of this study are; Laser Land Leveler (LLL), Zero Tillage (ZT) and Direct Seeded Rice (DSR). LLL is a - a machine equipped with a laser-operated drag bucket that ensures more flat, even surface in less time compared to the traditional ox-drawn scraper. A uniform field improves irrigation efficiency through better control of water distribution and reduces the potential for nutrient loss through improved runoff control, leading to greater efficiency of fertilizer use and higher yields. It is claimed that LLL will increase productivity, reduce water use and irrigation cost and decrease the emission of Green House Gases (GHGs). ZT is a cultivation practice that not only helps preserve soil fertility and conserves scarce water, but also boosts yields and increases farmers' profits by reducing their production costs. Instead of plowing their fields and then planting seeds, farmers who use zero tillage deposit seeds into holes drilled into the unplowed fields. In DSR, rice seed is sown and sprouted directly into the field, eliminating the laborious process of transplanting seedlings by hand and greatly reducing the crop's water requirement as compared to the traditional rice cultivation. In traditional rice cultivation, rice is first sprouted in a nursery; sprouted seedlings are then transplanted into standing water.

All three technologies are known for reducing variable costs such as labor and water input. However there is a capital investment cost (i.e., buying the machinery needed) or additional variable cost (i.e., renting the machinery) for implementing these technologies. These technologies promote sustainable intensification of agriculture and claim to increase mean productivity, and are generally considered risk reducing technologies. But they perform optimally only under certain conditions, such as with precise additions of complementary inputs. Deviations from these conditions may result in reduced yield benefits vis-á-vis the traditional technology, and thus have a perceived risk associated with their use. These technologies have been promoted by CIMMYT-CCAFS in three districts that define the study area for this research—Ludhiana in Punjab, Karnal in Haryana, and Vaishali in Bihar.

Theory:

The common approach to characterize risk preference is to use Expected Utility (EU) framework where the curvature of the utility function is solely defined by risk aversion. In prospect theory (PT) however, the shape of the utility function is jointly determined by three factors--risk aversion, loss aversion and a non-linear probability weighting measure. Risk aversion determines one's aversion to taking risk when the outcomes are positive. Loss aversion determines one's sensitivity to losses as compared to gains. Non-linear probability weighting measure determines ones tendency to overweight small probabilities and underweight large probabilities.

Though most papers in the past have focused on EUT as a framework to explain the role of risk in adoption I believe a more comprehensive analyses provided by PT might fit better in the context of this study for a number of reasons. First, most farmers are poor in our study area and they might be more sensitive to losses than to gains, so loss aversion could play a significant role. Second, in the proposed study area we will have a significant number of farmers who would be economically situated around the official poverty line and therefore might overvalue the probabilities around poverty line. Farmers who might just have moved out of the poverty trap, might be very cautious about investing in a new uncertain technology, because one failure might again throw them back to poverty. Third, if we take the concept of a target income towards which these farmers are trying to reach, they become more sensitive to loss than to gain when they are closer to the target income. Fourth, there is a possibility of status quo bias, also known as endowment effect, which indicates an individual's aversion to changing from a set behavior and is found to be an implication of loss aversion. As status quo bias explains brand loyalty, it could possibly also explain farmer's resistance to change (Liu 2013).

Ex ante, both PT and EU can act as a potential theory explaining farmer's decision making in regards to these new technologies. However, at this point it is not clear which one describes farmer's behavior better. I am therefore proposing to use Tanaka, Camerer and Nyugen (2009, hereafter TCN) design as it allows to estimate the empirical specifications that nest on both EU and PT. TCN model also allows the result from the experiments to determine whether PT or EUT fits the data better. TCN design has been tested in Vietnam, China (Liu, 2013) and India (Ward and Singh, 2015) with less educated farmers and it seems to be simple enough to follow.

Following TCN procedure the following utility function form is assumed.

$$U(x,p;y,q) = \begin{cases} v(y) + w(p)\big(v(x) - v(y)\big) & if \quad x > y > 0 \; or \; x < y < 0 \\ w(p)v(x) + w(q)v(y) & if \quad x < 0 < y \end{cases} \qquad \text{------------ 1}$$

Where

$$v(x) = \begin{cases} x^{\sigma} & for \quad x > 0 \\ -\lambda(-x^{\sigma}) & for \quad x < 0 \end{cases} \qquad \text{--------------2}$$

and $w(p) = exp[-(-lnp)^{\alpha}], \quad for \; 0<\alpha \leq 1$ --------------3

In the utility function, *x and y* are the outcomes and *p and q* are the probabilities associated with these outcomes. Parameter σ describes the curvature of the value function above zero. For an individual who is risk averse $\sigma < 1$, for a risk neutral individual $\sigma = 1$ and for a risk loving individual $\sigma > 1$. Risk aversion decreases in σ, *i.e. as* σ *increases risk aversion decreases.* Parameter λ, is the loss aversion parameter, which implies a kink in indifference curve around 0. High λ signifies that an individual is more loss averse. The non-linear probability weighting measure α comes from the model by Prelec (1998). *w(p*) shows the probability weighting function. If *α <0, w(p)* has an inverted S shape, which indicates an overweighting of low probabilities and underweighting of high probabilities. If the estimated results gives us *α=1 and λ =1,* then the above model reduces to EUT. However, our empirical holds prospects theory are true as suggested by the table 2 below, making a case for use of prospect theory for rest of the paper.

Prospect Theory Holds True			
Variable	Description	Mean	Std. Dev.
α	Probability weighting function parameter	0.693***	0.253
σ	Curvature of the prospect value function(risk aversion)	0.574***	0.335
λ	Measure of loss aversion	4.194***	4.089
(Null for σ =0, λ =1, α=1)			

Table 2

Conceptual Model

We have two lotteries; L^T, which represents the lottery under traditional farming methods and L^L, which represents the lottery under laser land leveler.

The lottery under traditional farming is as following

$$L^T = \begin{cases} 1 - f(G) \text{ that represents a good year and has a probability of } q \\ 1 - a\, f(G) \text{ that represents a bad year and has a probability of } (1-q) \end{cases}$$

Where 1= normalized profits per hectare using traditional leveler without the cost of incurred on irrigation.

f(G) is the cost incurred on irrigation and is a function of ground water level G.

a is the extra proportion of water pumped out of ground for irrigation in a bad monsoon year.

On the other hand we have the lottery under laser land leveler represented as

$$L^L = \begin{cases} 1 - C - n\, f(G) \text{ that represents a good year and has a probability of } q \\ 1 - C - n\, a\, f(G) \text{with represents bad year and has a probability of } (1-q) \end{cases}$$

Where the C is the cost of hiring laser land leveler and n is the proportion of water used on irrigation as compared to the traditional method. A smaller n means the laser land leveler is more efficient.

Now we plug the lotteries in the functional form of the utility function (as shown above) is as follows

The utility function for traditional lottery is $U(L)^T$

$$U(L)^T = w(q)\ v\big(1 - f(G)\big) + w(1-q)\ v(1 - af(G))$$

$$U(L)^T = \exp[-\,(-lnq)^{\alpha}]\,\big(1 - f(G)\big)^{(1-\sigma)} - \lambda \exp[-\,(-\ln(1-q))^{\alpha}]\,\big(1 - af(G)\big)^{(1-\sigma)}$$

and utility function for the lottery under laser land leveler $U(L)^L$

$$U(L)^L = \exp[-\,(-lnq)^{\alpha}]\,\big(1 - C - nf(G)\big)^{(1-\sigma)} - \lambda \exp[-\,(-\ln(1-q))^{\alpha}]\,\big(1 - C - naf(G)\big)^{(1-\sigma)}$$

We define the probability of adoption as a function of difference in the two utilities

As Prob $(L)^L$ =f ($U(L)^L - U(L)^T$)

Plugging in the functions for both the us we have

$$\Pr\,(L)^L = \mathrm{f}\quad \{\exp[-\,(-lnq)^{\alpha}]\,\big(1 - C - nf(G)\big)^{(1-\sigma)} - \lambda \exp[-\,(-\ln(1-q))^{\alpha}]\,\big(1 - C - naf(G)\big)^{(1-\sigma)} - \quad \exp[-\,(-lnq)^{\alpha}]\,\big(1 - f(G)\big)^{(1-\sigma)} + \lambda \exp[-\,(-\ln(1-q))^{\alpha}]\,\big(1 - af(G)\big)^{(1-\sigma)}\}$$

Next we define $\Pr\,(L)^L$ = F and take derivate of the function wrt risk aversion coefficient, loos aversion coefficient and probability weighting measure to know how does different risk measures affect adoption.

Plugging the values of C, a, f(G) and q from empirical data and the average values of risk version coefficient (σ), loss aversion coefficient (λ) and probability weighting measure (α) we have

$\frac{dF}{d\alpha}$ = -ve , i.e Farmers who overvalue smaller probabilities adopt more. This makes sense, because these technologies are considered to be risk reducing and farmers who overvalue smaller probabilities (of loss usually) are the ones who are more willing to adopt these technologies.

$\frac{dF}{d\sigma}$ = -ve i.e. More risk averse farmers adopt more. This falls in line with the risk-reducing idea associated with these climate smart technologies; a lower σ means lower risk aversion which causes less adoption. Alternatively higher risk aversion means higher technology adoption.

$\frac{dF}{d\lambda}$ = +ve i.e. More loss averse farmers adopt more. A greater λ means the farmer is more loss averse and the derivate suggests that with more loss aversion comes more technology adoption. This also, seems to be reasonable given the promoters of the technology consider them risk/loss-reducing.

We tests these theoretical findings with empirical data in the later section to find that they hold true.

Method: Field experiment design and procedure

To estimate the risk attitude variables (risk aversion coefficient, loss aversion coefficient and probability weighting measure), field experiments were conducted in the study area with a sample of farmers surveyed to measure the adoption of LLL, DSR and ZT technologies (data collection and sampling strategy described below). Field experiments involved playing lottery games with individual farmers (main decision maker of the household) who were selected for the adoption survey. Game participants were given three independent series of games that had a total of 35 pairwise choices. The first and second series contained 14 choices each and the third series had 7 choices between two lotteries: A and B. These two options (A and B) differ in the expected value of the lottery, which is a function of the probability of winning the noted cash value in a scenario of a random draw of a number between 1 to 10. The following table 1 shows all the 35 pairwise options and represents entire game's payoff matrix.

Table 1 - Payoff matrix of the game

Series 1	Option A			Option B		
Q. no	Rupees if you get 1,2,3	Rupees if you get 4,5,6,7,8,9 10		Rupees if you get 1	Rupees if you get 2,3,4,5,6,7,8,9 10	Q No.
1	40	10		68	5	1
2	40	10		75	5	2
3	40	10		83	5	3
4	40	10		93	5	4
5	40	10		106	5	5
6	40	10		125	5	6
7	40	10		150	5	7
8	40	10		185	5	8
9	40	10		220	5	9
10	40	10		300	5	10
11	40	10		400	5	11
12	40	10		600	5	12
13	40	10		1000	5	13
14	40	10		1700	5	14
Series 2	Rupees if you get 1,2,3,4,5,6,7,8,9	Rupees if you get 10		Rupees if you get 1,2,3,4,5,6,7	Rupees if you get 8,9,10	
15	40	30		54	5	15
16	40	30		56	5	16
17	40	30		58	5	17
18	40	30		60	5	18
19	40	30		62	5	19
20	40	30		65	5	20
21	40	30		68	5	21
22	40	30		72	5	22
23	40	30		77	5	23
24	40	30		83	5	24
25	40	30		90	5	25
26	40	30		100	5	26
27	40	30		110	5	27
28	40	30		130	5	28
Series 3	Rupees if you get 1,2,3,4,5	Rupees if you get 6,7,8,9,10		Rupees if you get 1,2,3,4,5	Rupees if you get 6,7,8,9,10	
29	25	-4		30	-21	29
30	4	-4		30	-21	30
31	1	-4		30	-21	31
32	1	-4		30	-16	32
33	1	-8		30	-16	33
34	1	-8		30	-14	34
35	1	-8		30	-11	35

For each of the 35 games (or rows in Table 1), respondents were presented with these two options and asked to select either Option A or Option B. For example, for series 1 (i.e., row 1) the respondents were presented with the following options:

Series 1	Option A			Option B		
Q. no	Rupees if you get 1,2,3	Rupees if you get 4,5,6,7,8,9 10		Rupees if you get 1	Rupees if you get 2,3,4,5,6,7,8,9 10	Q No.
1	40	10		68	5	1

It shows that lottery A offers a 30% chance of receiving Rs.40 and 70% chance of receiving Rs.10, whereas lottery B offers a 10% chance of receiving Rs.68 and 90% chance of receiving Rs.5. This decision to select Option A or Option B was repeated for each of the 35 rows in Table 1.

In series 1 and series 2, the expected value of lottery A does not change but as we proceed down, the expected value of lottery B keeps increasing and eventually exceeds the expected value of lottery A (Table 1). The aim of this game is to see at which row the subject shifts from option A to option B for series 1 (rows 1 to 14), series 2 (rows 15-28), and series 3 (rows 29-35). A more risk averse subject would choose lottery A for a greater number of iterations before shifting to B, as compared to a less risk-averse subject.

Following TCN's procedure, the subject is assumed to be rational, therefore he is allowed to switch from lottery A to lottery B only once in each series. There is a debate about the monotonic switching that it might make subjects choose option A for more iterations before he/she switches to option B. However, as monotonic switching has worked fine in TCN and Liu's experiment with subjects of similar educational background, it was also used in this study. The option of never switching is also available for each of the series. For example, a subject is free to choose lottery A for all 14 or 7 questions in any/all of the series or he can chose lottery B for all the rows for any/all of the series.

Once they complete their selection, there was a random draw of 35 numbered plastic chips to decide which game was played for real money. Once the game number (1 to 35) was selected, the next step was to select a random number between 1 to 10. For this the TCN method was followed by putting 10 numbered wooden chips (each numbered 1 to 10) in an opaque bag and then asking the farmer to draw one chip out of it to complete the randomization. For example, if the subject draws plastic chip number 1, and he has choosen lottery B for row 1, and a wooden chip number 7 is randomly drawn, he would earn Rs.5. However, if he chose lottery A for the same row, and number 7 is drawn, then he would earn Rs.10.

Switching points in each of the three series in Table 1 are useful in identifying the underlying behavioral parameters. The estimates of risk aversion coefficient (σ - that determines curvature of the utility function in the positive domain) and non-linear probability weighting measure (α) are simultaneously determined by the switching rounds in series 1 and series 2. These two series are carefully designed so that the pair of switching rounds from the two series can be used to identify the range for both σ and α, that are consistent with PT.

Series 3 has both positive and negative payoffs. It has seven choice scenarios, each of which comprise of two lotteries like earlier series. In each of the lottery there is a positive and a negative payout. The payouts vary across rows and are specified in a way that enables estimation of a range of possible loss aversion coefficient for each respondent.

The loss aversion parameter λ is determined by the switching point in series 3. Notice that λ cannot be uniquely determined from switching point in series 3 alone. Payoffs in series 3 are designed to make sure that λ takes similar values across different levels of σ. In calculating the λ, the probability weighting measure α drops out as the probability of getting positive or negative payout are equivalent in each round (p=0.5, q=0.5) and therefore the payoffs in series 3 must only correspond to different values of σ.

Since it would be unethical and impossible to have participating farmers pay from their own pocket, in case they lose money in the lottery, Rs.21 was given to each of the participating farmer at the beginning of the game. This was the maximum amount a subject can lose in the game. This also gave the farmer an ownership over the Rs. 21 and could better elicit the risk loss aversion behavior as now, it was his money that he was betting on.

Estimation of Parameters

For any participant who switches at row N, we can conclude that he prefers lottery A over B till row N-1 and at row N he prefers lottery B over lottery A. So we can get two sets of inequalities from this switching point. Using a combination of switching points from series 1 and series 2, yields a range of α and σ that satisfy this pair of inequalities.

For example suppose someone switches from lottery A to lottery B in row 7th in series 1. Then the following inequalities must be satisfied.

$$10^{\sigma} + \exp[-(-ln0.3)^{\alpha}]\,(40^{\sigma} - 10^{\sigma}) \quad > \quad 5^{\sigma} + \exp[-(-ln0.1)^{\alpha}](125^{\sigma} - 5^{\sigma}) \qquad (8)$$

$$10^{\sigma} + \exp[-(-ln0.3)^{\alpha}]\,(40^{\sigma} - 10^{\sigma}) \quad < \quad 5^{\sigma} + \exp[-(-ln0.1)^{\alpha}]\,(150^{\sigma} - 5^{\sigma}) \qquad (9)$$

The (σ, α) combinations that satisfy the above inequalities are (0.4,0.4), (0.5,0.5), (0.6.0.6), (0.7,0.7), (0.8,0.8), (0.9,0.9), (1,1).[1]

Similarly if the same person switches from A to B in row 7th in series 2, the following inequality holds true

$$30^{\sigma} + \exp[-(-ln0.9)^{\alpha}]\,(40^{\sigma} - 30^{\sigma}) \quad > \quad 5^{\sigma} + \exp[-(-ln0.3)^{\alpha}](65^{\sigma} - 5^{\sigma}) \qquad \text{-----}(10)$$

$$30^{\sigma} + \exp[-(-ln0.3)^{\alpha}]\,(40^{\sigma} - 30^{\sigma}) \quad < \quad 5^{\sigma} + \exp[-(-ln0.3)^{\alpha}](68^{\sigma} - 5^{\sigma}) \qquad \text{----}(11)$$

The (σ, α) combinations that satisfy the above inequalities are (0.8, 0.6), (0.7, 0.7), (0.6, 0.8), (0.5, 0.9) or (0.4, 1). By intersecting the parameters ranges from series 1 and series 2, we can obtain the approximate values of (σ, α) = (0.7, 0.7). Note that λ cannot be uniquely determined from switching in series 3. Payoffs in series 3 were designed to make sure that λ takes similar values across different levels of σ, which means for each switching point in series 3, we will have different values of λ based on the earlier found value of σ for that individual.

Data Source:

The risk experiments were designed by the author and conducted as part of a larger representative technology adoption surveys being undertaken by the Strengthening Impact Assessment in CGIAR (SIAC) project managed by Michigan State University. These surveys were conducted in three districts in India to assess the adoption of LLL, DSR and ZT. These three districts are—Ludhiana in Punjab, Karnal in Haryana and Vaishali in Bihar (Figure 1). The population of these districts range from 1.5 million in Karnal to 3.5 million in Ludhiana and Vaishali. These districts fall under the rice-wheat cropping system

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[1] σ and α are approximated to the nearest .05 increments.

and have been considered to be most developed agriculturally in their respective states. Over time there has been a series of interventions by various CGIAR institutions (especially, CIMMYT under the CCAFS program) and the state governments to introduce climate smart technologies.

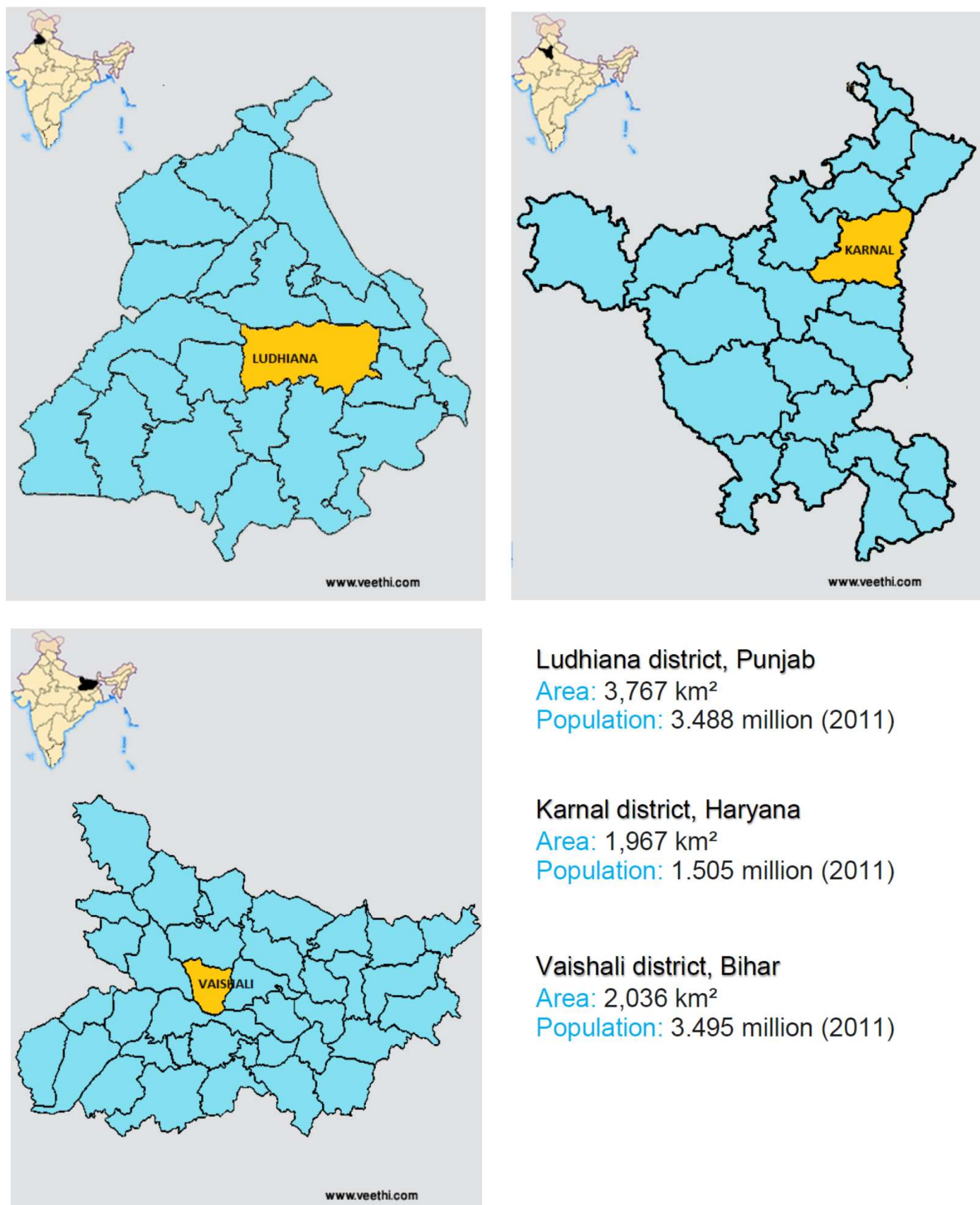

Figure 1. Location of three study districts

All the three districts included in the study have national or state level agricultural universities. While Ludhiana has one of the most prominent state agricultural universities of India, Karnal is home of the Indian Institute for Wheat and Barley Research of the Indian Council of Agricultural Research (ICAR), and Vaishali has been the testing ground for the Rajendra Agricultural University (also a part of ICAR). In summary, these three districts have always had new agricultural technologies available, though historically all three have fared differently in terms of technology diffusion and belong to states which are at different stages of agricultural and economic development (with Punjab and Haryana at a more developed end of the spectrum than Bihar).

For the broader adoption study, 80 villages each in these three districts were randomly selected from a list of all wheat growing villages using the probability proportionate to size (PPS) method (where size was measured by net sown area in the village as obtained from the last Census data). In each of these villages 10 households were selected randomly by the enumerators and a detailed questionnaire was administered to collect data on farmer and household characteristics, technology specific data for LLL, DSR and ZT, and adoption of other technologies by the household, and farmers' perception on constraints in wheat and rice farming. Data collection was done using a Computer Assisted Personal Interview (CAPI) method from a total of 2400 households across the three districts. The author participated in enumerator training, which took place in August-September 2015, followed by field survey from September to November 2015. The data collected correspond to Rabi 2014-15 and Kharif 2015 season.

Based on budget availability, risk experiments were conducted in a subset of villages in each district-- 28 villages in Vaishali, 14 villages in Karnal and 14 villages in Ludhiana. As there were 10 households selected randomly in each of the villages, we expect to have a total of 560 observations of risk experiments that will be used for this study.

Prior to conducting the experiment, enumerators explained the set of standardized instructions and asked questions to confirm whether the farmers understood the experiment. Next, before the real experiment, a round of practice experiment was conducted with candies as the payoff outcomes. This was conducted to make sure the farmers understood the rules of the game and how to note down their choices.

Econometric framework and preliminary results

There are two Econometric approaches this paper uses to find how risk measures impact the adoption of climate smart technologies. The first empirical approach is a simple probit

$$Y_L = \beta_0 + \beta_1 X_h' + \beta_2 R_h' + \mu_{hL}$$

Where Y_L is a latent variable based on the observable binary discrete choice of whether the farmer adopted and implemented the technology or not. X_h' includes access, institutional, plot, demographic and household characteristics, social capital etc., while R_h' includes risk attitude variables (risk aversion coefficient, loss aversion coefficient and probability weighting measure). The following table 3 shows the results for a probit model and a linear probability model with district fixed effects and both of them suggest that higher non-linear probability weighting measure (α) leads to lower adoption as suggested by our conceptual model. Farmers who overvalue smaller probabilities tend to adopt more. As α increases probability weighting measure decreases and adoption also decreases. This is likely when farmers who overvalue the small probabilities of loss tend to adopt technologies more. Risk aversion seems to have no significant effect on the adoption decision, while higher loss aversion does seem to increase the chances of adoption as suggested by our conceptual model. Farmers with higher loss aversion tend to adopt more. It is likely that farmers consider these technologies as risk/loss reducing therefore we see farmers who are more loss averse and farmers who want to avoid the smaller probabilities of loss tend to adopt it more. Plot characteristics, HH characteristics also seem to explain a major part of the tech adoption as suggested by literature.

VARIABLES	Probit (at means)	LPM (Dist. f.e)
Prob. Weighting Measure	-1.070***	-0.900*
Risk Aversion coefficient	0.392	0.374
Loss Aversion Coefficient	0.116***	0.062*
Age	-0.003	-0.002
Age*alpha	0.0216**	0.018
Age*Sigma	-0.00903	-0.01
Age*lambda	-0.00249***	-0.001*
HH poverty score	0.00253	0.001
Did you or anyone in the household access credit for ag. production	-0.107*	-0.1
Time it takes on average to travel to nearest commercial town	0.000438	0
Formal Education of Main Respondent	0.0121	0.008
Soil Quality(good)	0.304*	0.905***
Soil Type(Sandy)	-0.338**	-0.583***
Soil Type(Sandy Loam)	-0.125	-0.273**
Soil Type(Clay Loam)	-0.122	-0.183**
Soil Salinity(High)	0.315**	0.347***
Soil Salinity(Medium)	0.268***	0.315***
Soil Salinity(low)	0.197**	0.172*
Rsquared/ Pseudo R-squared	0.328	0.376

Table -3

However as probit is a latent variable model it just tells us whether someone adopted this technology or not. It does not differentiate between someone who adopted it 2 years after the release of the technology and someone who adopted 10 years after. Intuitively these two guys must be treated differently as one only waited 2 years and other 10 years, but probit does not allow us to do so. This inability of probit to capture the difference in timing of adoption creates an opportunity to use duration model. Using duration analysis we model how long does it takes the farmers to adopt the technology since their exposure to LLL. Here we model the time taken to adopt, as a function of different explanatory variables which also include risk parameters. Unlike in probit model, duration model does allow us to differentiate between someone who adopted LLL after 2 years of exposure and someone who adopted after 10 years of exposure.

In most studies using duration model, they model the time to adoption right from the time the technologies were releases, however this leads to serious endogeneity issues. Suppose a technology is release in the year 2010, and farmer A did not know about the technology till 2015, and after knowing in the year 2015 he/she adopted it in the year 2016. Another farmer B got to know about it in the year 2010 only, but waited for 6 years before he/she decided to adopt in 2016. So both farmers adopted in 2016, and if you do not have data on the time since they knew about the technology, one uses time since the technology is in the market as a proxy for "exposure time". To get rid of this problem we collected information on the "exposure time" by asking about their first exposure to the technologies and modelling this time from first exposure till adoption by duration analysis.

Prospect of adoption over time can expressed through the hazard rate.

h(t;x) =$h_0(t)\ e^{\beta' x}$

Indicating the probability of adoption in any given time period t, conditional on not having adopted up through time t - 1. Including the distribution of the hazard rate h(t) allows us to control for trends in "household time" t, as we estimate the effect of other household and external factors. The term incorporates the multiplicative effects of the vector of covariates on the hazard rate, including for an estimated intercept b, which can be multiplied by the hazard distribution $h_0(t)$ to get the "baseline hazard function." This baseline hazard is interpreted as the likelihood of the event of interest (the decision to adopt) occurring in time t if all other covariates were valued at zero. We do not have confirmed results for duration model yet, but preliminary results do show that loss averse farmers tend to adopt the technology sooner than others and also the farmers who overvalue smaller probabilities of losses tend to adopt the technologies sooner. This again falls in line with the scientific evidence associated with the promotion of these technologies.

Conclusion

Findings from this study suggest that farmers who are more loss averse and overvalue smaller probabilities of loss tend to adopt these technologies more. The findings are very informative as it shows what perception do farmers have of these technologies. Even though the promoter of this technology - CGIAR (Consortium General of International Agricultural Research) did consider these technologies as rick reducing there was no earlier evidence of the farmer's perception about these technologies. The findings of this study confirms the belief of CGIAR regarding these technologies are echoed by farmer's beliefs about them.

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