Do Smaller States Lead to More Development? Evidence from Splitting of Large States in India.

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Abstract:

Struggles for greater autonomy or more homogenous jurisdictions within a federal system has been a consistent phenomenon of the current nation states. However, there remains very little rigorous evidence of more autonomy and homogenous jurisdiction on development outcomes. Creation of three new states in India in the year 2000 allows us to test these development hypotheses. As states are the proximate determinants of local institutions driving development outcomes, a change in their boundaries provides us an opportunity to evaluate the impact of these shifts on the provision of public goods and distribution of development outcomes. We use quasi-experimental methods like difference in difference with parent state as comparison and newly formed state as treatment, alternatively we consider both the split states as two treatments with nearby states as comparison. Further, we use geographic discontinuity across the newly formed borders to show that districts in the newly created states are doing better on development indicators after splitting from their parent state.

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Risk Preferences and Climate Smart Technology Adoption:

A Duration Model Approach for India

Abstract

This paper examines the role of individual risk preferences in the decision of a climate smart technology in two northern states of India. We conducted a household survey and a field experiment using real cash with Indian farmers to elicit their risk preferences, and used them to explain their adoption of laser land leveler. The analysis extended the measurement of risk preferences beyond the expected utility theory to incorporate prospect theory. We use duration analysis approach to model the time to adoption and find that risk averse farmers and farmers who overvalue smaller probabilities adopt his technology sooner than others.

1. Introduction:

Climate change is expected to have widespread impacts on human and natural systems around the world. Agriculture is heavily dependent on weather conditions in most parts of the world, and therefore changes in temperature and precipitation regimes due to climate change are expected to impact this sector disproportionately more than other sectors (IPCC 2014). Technology is considered as a major driver of climate change adaptation in agriculture. Development of new crop varieties and animal breeds, and conservation agriculture and other climate smart technologies are expected to play a major role. In this paper we study the adoption of one such climate smart technology--Laser Land Leveler (LLL) in the Indian states of Punjab and Haryana.

LLL uses laser guided beams to level the fields with higher precision compared to traditional levelling. It is considered climate smart as it reduces water use and increases yield (Kaur 2012). For this reason, LLL is also first order stochastically dominates traditional leveling. For a region obsessed with higher yields and with rapidly declining stock of groundwater this technology seems an appropriate choice for most farmers. However, even after 15 years since its release, the technology has not been adopted by a significant population of farmers. Given such promising prospects, non-adoption or delay in the adoption of this technology by many farmers in this region calls for analysis of why this is the case.

In the context of agriculture generally, an extensive literature exists that explain why farmers do not adopt or delay adoption of new technology. Much of this literature cites low level of education (Foster and Rosenzweig, 1995), lack of information and access to credit (Barrett et al., 2004), learning spillovers (Munshi, 2004), tenure insecurity, small farm size, and unreliable supply of complementary inputs as the main constraints to technology diffusion. Further, there has been significant enquiry on the role of uncertainty about the effectiveness of a new technology as a major constraint to adoption (Feder, 1980). In most developing countries, agriculture is considered a risky proposition given its dependence on environmental factors that are beyond farmer's control. Furthermore, any new agricultural technology can have a wide distribution of outcomes, increasing the associated uncertainty. Thus, any new agricultural technology is inherently perceived as an uncertain proposition. Consequently, farmers' perceived uncertainty regarding effectiveness of the technology allows individual subjective risk preferences to play a major role in technology adoption (Holden, 2015).

Risk preferences have long been recognized as an important factor in explaining technology adoption. There are multiple reasons why it is important to account for individual risk preferences when studying technology adoption. First, omission of risk preferences is likely to bias significant variables like education and wealth, which are correlated with risk. Second, individual risk preferences have shown to be defining wealth accumulation and income growth (McInish, Ramaswami, and Srivastava, 1993). Third, Dohmen (2009) finds intergenerational correlation in risk preferences, which could explain the low level of intergenerational income mobility and wealth accumulation. As risk attitudes are not easily elicited by standard household surveys, the degree to which they play a role in wealth accumulation is less understood from an empirical perspective.

The common approach to illustrate an individual's risk attitudes is to use expected utility theory (EUT) approach where the curvature of the utility function is solely defined by risk aversion. We relax some of these restrictive assumptions inherent in EUT by incorporating aspects of prospect theory (PT) where the utility function is jointly defined by risk aversion, loss aversion, and non-linear probability weighting measure. While loss aversion measures one's sensitivity to losses as compared to gains, non-linear probability weighting measure captures individual's tendency of overvaluing small probabilities and undervaluing large probabilities. We believe that PT might explain individual decision-making behavior better than EUT as it captures loss aversion and non-linear probability weighting measure, in addition to risk aversion.

We develop a simple technology adoption model that includes risk preferences. Considering uncertainty regarding LLL as a major inhibiting factor for its adoption we allow subjective risk preferences of the farmers regarding its effectiveness in reducing irrigation cost and increasing yield to be different from objective risk preferences. The model assumes that subjective beliefs of the farmers about the effectiveness of LLL in reducing water use for irrigation and their subjective belief of future rainfall will determine their adoption decision. The model predicts that if the farmers perceive LLL as more effective in reducing water cost and increase yield as claimed by the scientists, then more risk averse farmers would adopt it sooner. Alternatively, if the farmers considered this technology as not very effective in reducing water cost and increasing yield then they would delay adoption.

This paper is organized as follows. Section 2 covers the literature review. Section 3 provides information on the laser land leveler technology and describes the survey and dataset. Section 4 explains the design of the field experiment and presents descriptive analysis. In Section 5 a conceptual framework is used to describe the role of risk preferences in technology adoption decisions. Section 6 provides a general econometric framework to test the predictions and describes the empirical results. Section 7 concludes the paper

2. Literature Review

Binswanger et al. (1980) elicited the risk preferences of a sample of Indian farmers using 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. Holt and Laury (2000) showed that even when payoffs were small, subjects exhibited risk aversion, and when they were scaled by factors of twenty, fifty, and ninety it made little difference when the high payoffs are hypothetical. In contrast, subjects become sharply more risk averse when the high payoffs are actually paid in cash suggesting subjects facing hypothetical propositions cannot imagine how they would behave under real incentive conditions and therefore gambling game techniques using real cash elicits more accurate risk preferences.

Most studies on role of risk aversion in technology adoption have used EUT framework, where the shape of the utility function is solely defined by risk aversion. However, there is a growing literature suggesting that expected utility theory does not provide a plausible theory of risk aversion for both small-stakes and large-stakes gambles and this decision theory should be replaced with an alternative theory characterized by loss aversion and non-linear probability weighting measure (Cox & Vjollca, 2001, Rabin 2000). Kahneman and Tversky(1979) in their seminal work developed Prospect Theory(PT) as an alternate model to describe decision making under risk, in which value is assigned to gains and losses rather than to final assets, and probabilities are replaced by decision weights. As PT allows for more flexibility and seems to be closer to actual decision making under risk, we use this framework to explain risk preferences of farmers. In choosing PT we do not reject EUT completely, as the latter is a special case in PT when loss aversion is same as risk aversion and non-liner probability weighting measure does not matter. Using PT we do a comprehensive testing of roles of risk aversion, loss aversion and probability weighted measure in technology adoption decision for LLL.

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 the 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. Building on their work, this paper also uses all three risk parameters in explaining technology adoption decision. To our knowledge, this is the first study that examines the role of risk preference in the explaining the adoption of a climate smart technology which is considered to be and promoted as risk reducing among scientific and development community.

3. Background on Laser Land Leveler and the Technology Adoption Survey:

3.1 Background of Laser Land Leveler

Traditionally farmers in India, level their land after ploughing and before sowing to allow flood irrigation water to evenly spread across the field. LLL is a machine equipped with a laser-operated drag bucket that ensures more flat, even surface in less time compared to the traditional scraper. A more even land means irrigation water reaches every part of the field with minimal waste from water run-off or water-logging. This ensures that farmers use water more efficiently. It also reduces potential nutrient loss through improved runoff control, leading to greater efficiency of fertilizer use and higher yields. Use of laser land leveler reduces emission of greenhouse gases through decreased water pumping time, decreased cultivation time and better use of fertilizers (Aryal et al. 2015). Success of LLL has been well documented in a paper by Jat et al. (2009) where they show that LLL improves rice-wheat (RW) cropping-system productivity by 7.4% as compared to traditional land leveling. Total irrigation water savings under LLL versus traditional leveling were estimated to be 12–14% in rice and 10–13% in wheat. LLL improved per hectare profitability of the RW cropping-system from US$113 to $175. The technology is well suited for smallholder farmers as it does not require any major investment. Almost all the farmers using LLL, rent it for a nominal charge equivalent to a few days of rural wages which is quite affordable. The learning curve for farmers to use this technology is not very steep as the method of traditional leveling is very similar to LLL. Given these superior characteristics and success of LLL in field trial by agronomists, it is quite puzzling to see that a significant proportion of farmers have still not adopted this technology. In conversation with experts prior to the field survey, most cited uncertainty about the technology as one of the main reasons for the low farmer adoption of this technology.

3.2 Survey procedure

The risk experiments were designed by the authors and conducted as part of a larger representative adoption surveys. These surveys were conducted in several districts in India to assess the adoption of LLL and other natural resource management technologies. The two districts focused by this study are—Ludhiana in Punjab, and Karnal in Haryana. These districts fall under the rice-wheat cropping system and have been considered to be most developed agriculturally in their respective states and the entire country. 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, including the LLL in these two districts.

Both the 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). In summary, these two districts have always had new agricultural technologies available and historically have led the country in terms of technology diffusion and adoption.

For the broader adoption study, 80 villages each in these two 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, adoption of other technologies by the household, and farmers' perception on constraints in wheat and rice farming. Data collection was done from September to November 2015 using a Computer Assisted Personal Interview (CAPI) method from a total of 1600 household across the two districts. Agricultural data that was collected corresponded to Rabi 2014-15 and Kharif 2015.

3.3 Data Description

Based on budget availability, risk experiments were conducted in a subset of villages in each district-- 29 villages in Karnal and 25 villages in Ludhiana leading to an overall sample of 432 ouseholds. 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.

Table 1 shows the summary statistics for the variables of interest for the households that participated in the experiments. The average farmer is around 42 years old at the time of the survey and has 9.43 years of formal education. This is expected as the study districts are in an advanced part of India and farmers are likely to be more educated. The farmers are well to do in this region with an average land holding of 9.43 acres (3.7 hectares) and the average household poverty score on a scale of 0-100 is close to 67, which implies less than 10% probability that a typical household included in our survey is living below poverty line. The average household size is 5.95 and the average number of working member is 2.44, which is usual in rural India. From the total 481 households, 432 households or close to 90% had heard about the Laser Land Leveler technology, and of these 432, 67% had adopted it. For explaining time to adoption, we use these 432 households who have heard about the technology.

4. Field Experiment Design and Procedure

4.1 Experiment Design

Ex ante, both PT and EUT can act as a potential theory explaining farmer's decision making in regard to this new technology. However, at this point it is not clear which one describes farmer's behavior better. We therefore propose to use Tanaka, Camerer and Nyugen (2009, hereafter TCN) design as it allows to estimate the empirical specifications that nest on both EUT 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.

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

Where

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

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

In the above 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 a risk averse individual $\sigma < 1$, 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, that defines the shape of the value function below zero comparative to the value function above zero. If *λ=1* then there is no kink in the curvature of the value function around 0, suggesting that individuals treat losses similar to gains, however if $\lambda \neq 1$ indicates a kink. $\lambda > 1$ implies a more convex shape of the value function below zero suggesting individuals are more averse to loses than to gains. The non-linear probability weighting measure α comes from an axiomatically derived weighting function model by Prelec (1998). *w(p)* shows the probability weighting function. $\alpha < 1$ suggests an inverted S shaped *w(p),* indicating overweighting of low probabilities of larger losses or gains and underweighting of higher probabilities. If the estimated results give us *α=1 and λ =1,* then the above model reduces to EUT. However, our empirical results holds prospects theory is true as suggested by table 2, making a case for use of prospect theory for rest of the paper.

4.2: Field experiment 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. 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. Table 1 shows all the 35 pairwise options and represents entire game's payoff matrix.

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

The above table shows the row 1 of series 1 of the lottery was presented to the individuals. 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 all three series 1, series 2 and series 3 option A is always less risky compared to Option B. For both series 1 and 2, the expected value of lottery A does not change but as we proceed down, the expected value of lottery B keeps monotonically increasing and eventually exceeds the expected value of lottery A (Table 1). We are interested in knowing at which row does the individual 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 individual would choose lottery A for a greater number of iterations before shifting to B, as compared to a less risk-averse individual.

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 choose lottery B for all the rows for any/all of the series.

Individuals were told that one of the 35 rounds will be randomly chosen ex post and the lottery chosen will be played for actual cash. With this information, the individuals were asked to chose between option A and option B for all the 35 rows. 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 chosen 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 loss aversion behavior as now, it was his money that he was betting on. We find average of σ as 0.64 suggesting farmers in the sample in general are risk averse. The average of α = 0.70 implying farmers seem to overvalue smaller probabilities of high impact gains/losses. The average of λ = 3.13, indicating a kink in the values function around 0, with steeper declines in prospect value in the loss compared to the inclines under gains All three risk parameter average values are close to values found in other studies done by Liu in China and Ward in Eastern India.

4.3 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.

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

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

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 follow TCN's convention of approximating σ and α by taking the midpoint of the interval to one decimal place.

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

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

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

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.

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

5. 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 in a good monsoon year and a bad monsoon year. The idea is that in a bad monsoon year, there is more labor needed for irrigation.

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

Where 1= normalized revenue per hectare.

f(w)= Labor Cost incurred on irrigation as a function of labor wages w.

I(k)= Cost of other inputs as a function of prices of other inputs k.

a= extra labor cost as a proportion, due to a bad monsoon year. The idea is that if the monsoon is bad, there is more labor needed for irrigation.

On the other hand, we have the lottery under laser land leveler represented as following. Again, the probability of good and bad monsoon year is q and 1-q respectively. Additionally, now we have subjective beliefs of the farmers about the technology. We assume that the farmer expects that with a probability of *p* the farmer thinks that the technology will succeed and with a probability of *(1-p),* that the technology will fail.

L^L

$$= \begin{cases} X - s\,f(w) - I(k) - c \quad good\ year\ and\ the\ farmer\ thinks\ tech\ is\ successful = \ probability\ of\ pq \\ 1 - \ f(w) - I(k) - c \quad good\ year\ and\ the\ farmer\ thinks\ tech\ is\ failure = \ probability\ of\ (1-p)q \\ 1 - \ a\,f(w) - I(k) - c \ \ bad\ year\ and\ the\ farmer\ thinks\ tech\ is\ failure = \ probability\ of\ (1-p)(1-q) \end{cases}$$

Where

X= Higher proportion in income due to use of LLL when the farmer thinks the technology is successful

s= saving of labor input as a proportion due to use of LLL. s< 1

c= cost of hiring LLL per hectare.

Now let us take outcome $1 - \ f(w) - I(k) - c$ as the base case

So, we have

$$L^L = \begin{cases} X((1-s)f(w)\,) \ \ with\ probability\ of\ pq \\ 0 \ \ with\ \ probability\ of\ (1-p)q \\ (1 - \ a)f(w)\ with\ \ probability\ of\ (1-p)(1-q) \end{cases}$$

and

$$L^T = \begin{cases} c \ \ with\ a\ probability\ of\ q \\ c \quad + (1-a)\ f(w)\ with\ a\ probability\ of\ (1-q) \end{cases}$$

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 $U(L)^T$

$U(L)^T = w(q)\ \ v(c) + w(1-q)\ \ v(c \quad + (1-a)\ f(w)) = \exp[-\,(-lnq)^{\alpha}]\,(c)^{(\sigma)} - \lambda$

$\exp[-\,(-\ln(1-q))^{\alpha}]\,(c \quad + (1-a)\ f(w))^{(\sigma)}$

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

$$U(L)^L = \exp[-(-lnpq)^{\alpha}]\,(X((1-s)f(w)) - \lambda \exp[-(-\ln(1-\mathrm{p})(1-q))^{\alpha}]\ (1-\ a)f(w)^{(\sigma)}$$

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 functional form of both the utility functions we have

$$\Pr(L)^L = \left[\exp[-(-lnpq)^{\alpha}]\,(X((1-s)f(w)) - \lambda\ \exp[-(-\ln(1-\mathrm{p})(1-q))^{\alpha}]\ (1-\ a)f(w)^{(\sigma)}\right] -$$
$$\exp[-(-lnq)^{\alpha}]\,(c)^{(\sigma)} + \lambda \exp[-(-\ln(1-q))^{\alpha}]\,(c\ \ + (1-a)\ f(w))^{(\sigma)}$$

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.

6. Econometric Framework and Results

6.1 Econometric Framework

In this section, the main variable of interest is the time it takes to adopt. Since, we have the retrospective data on the year of release (i.e., 2011), year when the farmers got aware about the technology and the year farmers adopted it, duration model provides a natural framework for modeling adoption probabilities (Kiefer, 1988). Most studies using survival analysis to model time to adoption, use the release of the technology as the base year and assume that there is no heterogeneity in information dissemination of the technology. Estimating a single duration of adoption without accounting for diffusion duration raises econometric issues such as endogeneity (Ahsanuzzaman and Maredia, 2018). A farmer who has endogenously better access to information, say who is leader of a group, is expected to be aware of the technology earlier than other farmers. This, however, does not necessarily indicate that the same farmer is more likely to adopt the technology earlier than the other farmers.

. While estimating adoption duration, the omission of diffusion time might be due to unavailability of the information about the diffusion duration. However, we have data on both the duration of diffusion (time it took for farmer to know about LLL) and adoption duration (time it took to adopt once the farmer got to know about it). We model the later duration as this is the period when the farmer is actually exposed to the technology.

Let *t* be the time elapsed from the time of first exposure to Laser Land leveler adoption, $X_i(t)$ be a vector of relevant explanatory variables, and β be a vector of coefficients. Denoting the cumulative density function as $F_i(t|X_i, \beta) = Prob(T \leq t|X_i, \beta)$ and the density function as $f_i\,(t \mid X_i\,, \beta)$. The hazard function indicating the probability of adopting LLL at period t conditional on not having adopted it till time *(t-1)* is defined by $h_i\,(t\,|X_i\,, \beta\,) = f_i\,(t \mid X_i\,, \beta\,)/[1 - F_i(t|X_i, \beta)]$.

The general form of proportional hazard function is

$$h_i(t|X_i(t), \beta) = h_0(t)\exp\{X_i'(t)\beta$$

Where the baseline hazard is h_0 and X's are the explanatory variables. I use a Weibull baseline hazard specification to test if the hazard is time dependent. For more intuitively interpretable results, the above hazard rate can be parameterized into what is known as the Accelerated Failure Time (AFT) model, a simple transformation of the proportional hazards model, which is what we use. Under AFT we have to take exponential of the β to interpret the coefficients. In vector form, the AFT model can be expressed as

$\log(t)$=$\beta' X + \sigma\varepsilon$

where t is a non-negative random variable denoting adoption time, X is the vector of explanatory variables, and β is the vector of corresponding coefficients. In the case of a Weibull hazard function, ε is the error term that follows an Extreme value distribution.

6.*2 Results*

The results of the estimates are the standard errors of the duration model for "exposure time" of LLL adoption is presented in Table 3. We model the Exposure time as the time farmers took after they knew about the technology. State and village fixed effects are controlled for in all specifications. The main characteristic of interest is individual risk preference. In the existing literature, most studies do not have any control for individual risk preference; therefore, the regression result in Column 1 excludes the risk preferences parameter as a comparison. Column 2 show results on time to adoption once the farmer is aware about the technology, and column 3 show results on time to adoption from release of the technology. It is apparent that the results from column 3 underestimate the effect of risk parameters due to missing information on time for diffusion. Column 2 results takes care of temporal heterogeneity in diffusion.

To interpret the coefficients, one needs to exponentiate coefficients reported in the table obtaining hazard ratios. For example, to interpret the coefficient of σ in Column 2, we need to exponentiate (0.188) = 1.21. This implies that the risk-averse individual with σ = 0 in the sample is 21% more likely to adopt Laser Land Leveler than the risk-neutral individual (σ = 1) at any given time. Similarly, an individual who overvalues smaller probability (α=0) is 20% more likely to adopt LLL at any given time (Exp[0.185]). α defines the shape of the probability weighting function and a smaller α indicates an individual's tendency to overweight small probabilities.

An increase in income from wheat-rice crops as a proportion of total income leads higher probability of adoption. Age at the time of adoption and education both have negative coefficient, but are not significant. Higher number of plots increases the makes a farmer more likely to adopt the technology. This study does not have a detailed social network module like one in Conley and Udry (2010), which can be a concern given networks might be correlated with risk preference and social network is also correlated with technology adoption. I use self-reported proxies for network; the number of farmers the respondent interacts with and the results clearly show how smaller the social network of the farmer, lower are his probabilities of adoption. We also, control for religious affiliations, which is another major foundation of social network. The results show that a Muslim one is 145% less likely to adopt LLL compared to a Hindu farmer.

Another interesting result is the role of government extension in adoption. If the farmer gets the information from government extension his probability of adoption increases by 19% (Exp[-.206]), suggesting the higher trust farmers put in information from public sources compared to private sources. Further, the coefficient for "time from release to awareness" is negative suggesting if the farmer takes one year longer to know about the technology, he is 9% (Exp[-.0888]) more likely to adopt shortening his time to adopt. This is expected, because if the farmer hears about the technology later, he is likely to get more credible information as more people around him would have adopted and their experiences will bring him more rich information.

There are two limitations of this study that we would like to highlight. First, an underlying assumption of the duration model is that all the farmers will eventually adopt this technology. Experts and farmer leaders we have consulted compare this technology with the tractor and rotavator that most farmers in this two districts have now adopted. They predict that LLL technology will be also eventually adopted by most farmers. Second, our data is cross-sectional that raises the concern that any ex-post measurement of explanatory variables could be affected by the adoption decision, and they are therefore endogenous (Besley and Case, 1993). Our explanatory variables, however, are unlikely to be endogenous as most of them are time invariant. We have data on land owned by farmers in the last 15 years and it hardly shows any variation, suggesting that land size at the time of the survey is a good proxy for land at the time a farmer got aware about the technology.

6.3 Robustness Check

In this sample 5.6% of the farmers always chose either option A or option B for all of their choices in the game. They might have chosen so because of their inherent risk preference or because they did not understand the game properly. Assuming they did not understand the game, we exclude them from the regression and still find very similar results as indicated in column 4 of table 5. Similarly, it is possible that some of the farmers did not remember the exact year they heard about LLL or misreported it, leading to measurement error. In column 2 of table 5 we define the first time a farmer gets to know about a technology as the year when it was first used by someone in the village and we get very similar results to our original specification. The results do not change by clustering at the village level or excluding the 7 farmers who dis-adopted LLL. Credit constraints for adoption decisions are less likely to play a role in wealthier farm households, and as a result, the estimate bias should be minimal among those households. We restrict the sample to the top one-third wealthier households as shown in column 5, and we find that risk aversion is still significant while probability weighting does not, suggesting credit constraint is less likely to play a role in adoption decision.

7. Conclusion

Researchers and governments have long promoted the LLL technology as risk reducing. The findings of this study confirm this characterization of the technology by showing that once becoming aware, farmers who are more risk averse and overvalue smaller probabilities have a higher probability of adopting the Laser Land Leveler at any given time. In other words, farmers who are more risk averse and who overvalue smaller probabilities adopt this technology sooner compared to farmers who are risk neutral/loving and farmers who do not over value smaller probabilities.

Since on average farmers are risk averse, the findings of this study have two important implications. First, for a risk reducing technology such as LLL, farmer's aversion to risk is not a limiting variable but an inducing factor in promoting the adoption of this technology. This is contrary to the relationship of risk perception and adoption of other types of agricultural technologies. Second, the delay in adoption observed in these two progressive districts, is partly explained by the slow rate and speed of diffusion and awareness of this technology. Efforts to promote the diffusion of this and other risk reducing technology using public and private extension channels and diverse modes of information delivery should receive greater attention to help speed up the adoption of such risk reducing climate smart technologies.

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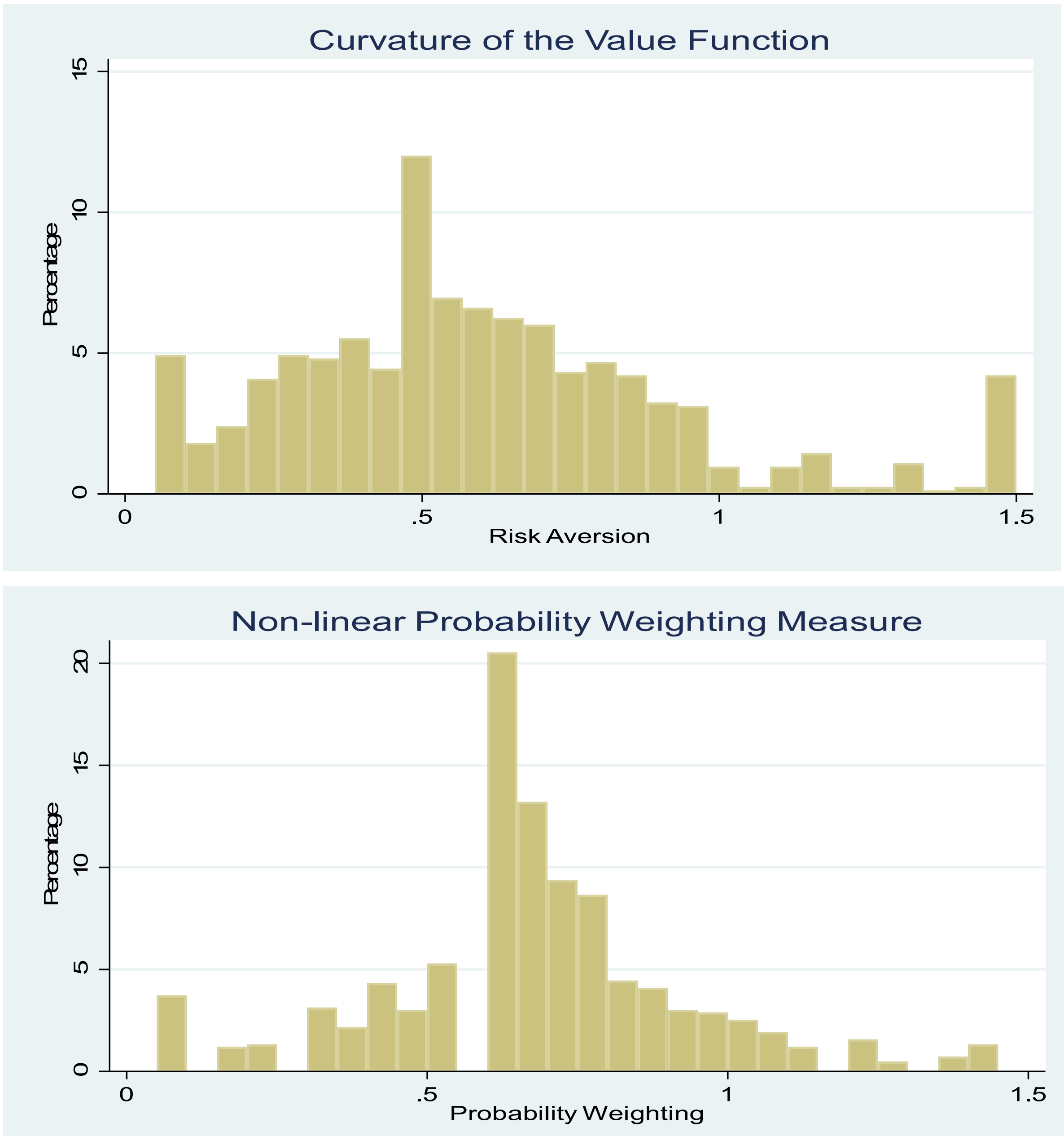
Figure 1 : Distribution of Risk Preference Parameters



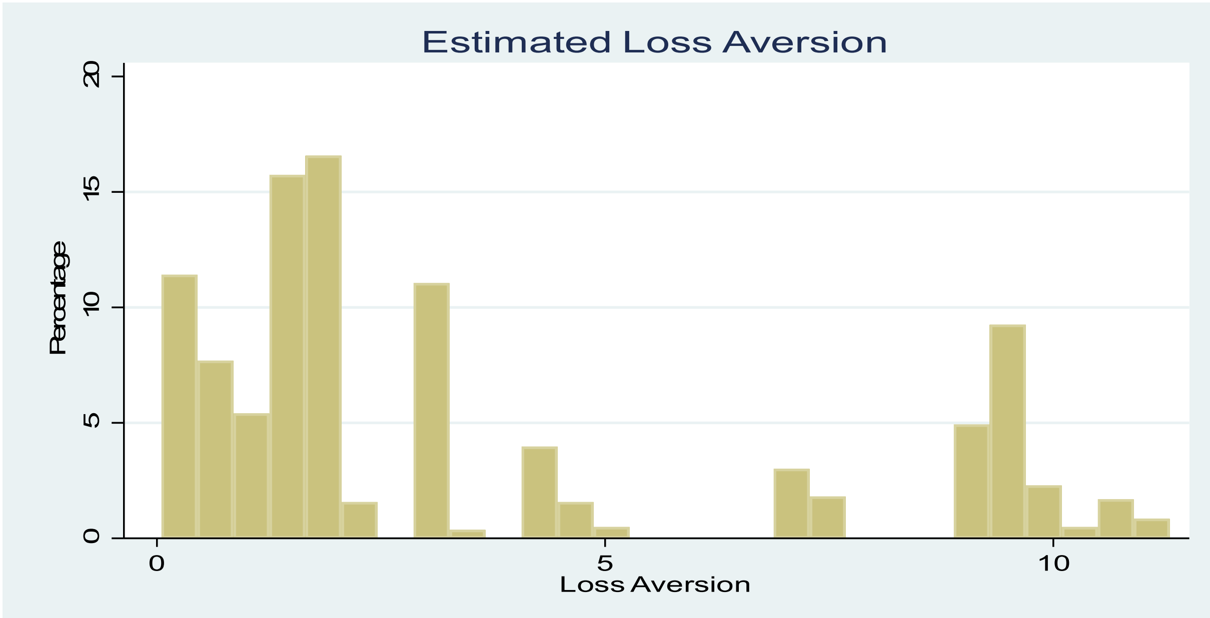

Estimated Loss Aversion
Percentage
0
5
10
15
20
0
5
10
Loss Aversion

Table 1- Summary Characteristics

	Summary Statistics
Risk Aversion	0.64
	(0.30)
Loss Aversion	3.13
	(2.92)
Non-Linear Probability Weighting Measure	0.70
	(0.22)
Age	42.24
	(12.9)
Education (Years)	9.43
	(3.46)
Household Poverty Score	67.37
	(11.25)
Land Owned in Acres	9.32
	(10.49)
Number of plots	1.16
	(0.37)
Distance to the nearest Agriculture Extension Centre(KM)	10.88
	(9.22)
Number of Mobile Phones in the household	2.48
	(0.92)
Number of Siblings of the head of the household	3.2
	(2.25)
Total Working Member	2.44
	(1.68)
Proportion using mobile for info. on Agriculture	0.28
	(0.45)
Proportion getting advice from Farmer's groups	0.55
	(0.5)
Self-reported value of total Asset (in Indian Rupees)	558203
	(421952)
Average distance to Plot(KM)	1.54
	(2.62)
Self-rated risk attitude (1= Most adventurous, 4= least Adventurous)	2.22
	(0.88)
Household Size	5.95
	(2.18)
Proportion of farmers who have heard of LLL	0.9
	(0.3)
Proportion of farmers who have adopted LLL if heard (N=416)	0.69
	(0.46)
Observations	432

Note: Standard Deviations are in parenthesis

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Table 2

Payoff Matrix for the Experimental Game

Series 1	Lottery A	Lottery B
1	30% chance of winning Rs.40 and 70% chance of winning Rs.10	10% chance of winning Rs.68 and 90% chance of winning Rs.5
2	30% chance of winning Rs.40 and 70% chance of winning Rs.11	10% chance of winning Rs.75 and 90% chance of winning Rs.5
3	30% chance of winning Rs.40 and 70% chance of winning Rs.12	10% chance of winning Rs.83 and 90% chance of winning Rs.5
4	30% chance of winning Rs.40 and 70% chance of winning Rs.13	10% chance of winning Rs.93 and 90% chance of winning Rs.5
5	30% chance of winning Rs.40 and 70% chance of winning Rs.14	10% chance of winning Rs.106 and 90% chance of winning Rs.5
6	30% chance of winning Rs.40 and 70% chance of winning Rs.15	10% chance of winning Rs.125 and 90% chance of winning Rs.5
7	30% chance of winning Rs.40 and 70% chance of winning Rs.16	10% chance of winning Rs.150 and 90% chance of winning Rs.5
8	30% chance of winning Rs.40 and 70% chance of winning Rs.17	10% chance of winning Rs.185 and 90% chance of winning Rs.5
9	30% chance of winning Rs.40 and 70% chance of winning Rs.18	10% chance of winning Rs.220 and 90% chance of winning Rs.5
10	30% chance of winning Rs.40 and 70% chance of winning Rs.19	10% chance of winning Rs.300 and 90% chance of winning Rs.5
11	30% chance of winning Rs.40 and 70% chance of winning Rs.20	10% chance of winning Rs.400 and 90% chance of winning Rs.5
12	30% chance of winning Rs.40 and 70% chance of winning Rs.21	10% chance of winning Rs.600 and 90% chance of winning Rs.5
13	30% chance of winning Rs.40 and 70% chance of winning Rs.22	10% chance of winning Rs.1000 and 90% chance of winning Rs.5
14	30% chance of winning Rs.40 and 70% chance of winning Rs.23	10% chance of winning Rs.1700 and 90% chance of winning Rs.5
Series 2	Lottery A	Lottery B
1	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.54 and 30% chance of winning Rs.5
2	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.56 and 30% chance of winning Rs.5
3	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.58 and 30% chance of winning Rs.5
4	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.60 and 30% chance of winning Rs.5
5	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.62 and 30% chance of winning Rs.5
6	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.65 and 30% chance of winning Rs.5
7	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.68 and 30% chance of winning Rs.5
8	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.72 and 30% chance of winning Rs.5
9	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.77 and 30% chance of winning Rs.5

10	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.83 and 30% chance of winning Rs.5
11	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.90 and 30% chance of winning Rs.5
12	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.100 and 30% chance of winning Rs.5
13	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.110 and 30% chance of winning Rs.5
14	90% chance of winning Rs.40 and 10% chance of winning Rs.30	70% chance of winning Rs.130 and 30% chance of winning Rs.5
Series 3	Lottery A	Lottery B
1	50% chance of winning Rs.25 and 50% chance of losing Rs.4	50% chance of winning Rs.30 and 50% chance of losing Rs.21
2	50% chance of winning Rs.4 and 50% chance of losing Rs.4	50% chance of winning Rs.30 and 50% chance of losing Rs.21
3	50% chance of winning Rs.1 and 50% chance of losing Rs.4	50% chance of winning Rs.30 and 50% chance of losing Rs.21
4	50% chance of winning Rs.1 and 50% chance of losing Rs.4	50% chance of winning Rs.30 and 50% chance of losing Rs.16
5	50% chance of winning Rs.1 and 50% chance of losing Rs.8	50% chance of winning Rs.30 and 50% chance of losing Rs.16
6	50% chance of winning Rs.1 and 50% chance of losing Rs.8	50% chance of winning Rs.30 and 50% chance of losing Rs.14
7	50% chance of winning Rs.1 and 50% chance of losing Rs.8	50% chance of winning Rs.30 and 50% chance of losing Rs.11

Table 3. Prospect Theory vs Expected Utility Theory

Prospect Theory Holds True			
Variable	Description	Mean	Std. Dev.
α	Probability weighting function parameter	0.704***	0.222
σ	Curvature of the prospect value function (risk aversion)	0.643***	0.307
λ	Measure of loss aversion	3.127***	2.918
(Null for σ =1, λ =1, α=1)			

Table 4- Weibull Model for Duration of Time to Adoption

VARIABLES	(1)	(2)	(3)
Risk Aversion		0.188*	0.0453*
		(0.111)	(0.0252)
Probability Weighting		0.185*	0.0424*
		(0.107)	(0.0232)
Loss Aversion		-0.00454	-0.00212
		(0.00897)	(0.00247)
Age	-0.00159	-0.00132	-0.000127
	(0.00305)	(0.00456)	(0.000731)
Education(Years)	-0.0132	-0.0132	-0.00255
	(0.0109)	(0.0138)	(0.00249)
Percentage of Income from Wheat-Rice	-0.00403*	-0.00441*	-0.00104**
	(0.00216)	(0.00226)	(0.000509)
Household Poverty Score	-0.00371	-0.00402	-0.000909
	(0.00314)	(0.00361)	(0.000719)
Land Owned Acres	-0.00175	-0.00166	-0.000343
	(0.00239)	(0.00361)	(0.000619)
Number of Wheat-Rice Plots	-0.151**	-0.150*	-0.0349**
	(0.0679)	(0.0823)	(0.0147)
Distance to Nearest Agricultural Ext. Centre	-0.0110	-0.00847	-0.00267
	(0.00895)	(0.00659)	(0.00217)
Number of siblings	-0.0127	-0.0159	-0.00454
	(0.0188)	(0.0179)	(0.00433)
Percentage Area Sandy-Loamy	0.0991	0.101	0.0296
	(0.1000)	(0.106)	(0.0239)
Total Working member	-0.00423	-0.00647	-0.000118
	(0.0154)	(0.0164)	(0.00357)
Whether use mobile for info on Agri.	-0.105	-0.122	-0.0267
	(0.0764)	(0.0922)	(0.0184)
Whether gets info from farmer's group	-0.0585	-0.0209	0.00178

		(0.116)	(0.128)	(0.0271)
Religion	1. Muslim	0.821**	0.896***	0.125*
(Base Hindu)		(0.339)	(0.333)	(0.0754)
	2. Sikh	-0.0951	-0.140	-0.0336
		(0.187)	(0.160)	(0.0422)
	3. Others	-0.233	-0.310	-0.0765
		(0.364)	(0.194)	(0.0819)
Source of Info- Government Extension		-0.236**	-0.206*	-0.0590**
(Base- Private)		(0.117)	(0.118)	(0.0269)
Average Distance to Plot (KM)		-0.0230**	-0.0262**	-0.00526***
		(0.00963)	(0.0113)	(0.00156)
Interaction with no. of Farmers	1. (75-100)	0.155	0.185	0.0455
Base (100+)		(0.245)	(0.237)	(0.0418)
	2. (50-75)	-0.0631	-0.0188	-0.0135
		(0.291)	(0.269)	(0.0565)
	3. (30-50)	0.305	0.363	0.0749
		(0.291)	(0.291)	(0.0577)
	4. (20-30)	0.359	0.453*	0.0966
		(0.290)	(0.273)	(0.0589)
	5. (10-20)	0.544*	0.621**	0.141**
		(0.308)	(0.313)	(0.0642)
	6. (0-10)	5.800***	5.845***	1.345***
		(0.493)	(0.721)	(0.110)
Time from release to Awareness (years)		-0.0888**	-0.0854*	0.0609***
		(0.0380)	(0.0495)	(0.00958)
Whether adopts early(self-reported)		-0.0969	-0.0453	-0.0136
		(0.121)	(0.155)	(0.0293)
State - Haryana		-1.336***	-1.376***	-0.281***
(Base Punjab)		(0.387)	(0.307)	(0.0895)
Constant		3.649***	3.323***	2.305***
		(0.742)	(0.871)	(0.169)
Observations		432	432	432

Note: All regressions include Village fixed effects. Standard errors clustered at Village level
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Weibull Model for Duration of Time to Adoption: Robustness Check

VARIABLES	Cluster	Village	Ex-Disadopters	Ex-No Switch	Top one third
Value function curvature	0.249***	0.288***	0.204**	0.217*	0.426*
	-0.0846	-0.105	-0.0404	-0.11	-0.241
Probability Weighting	0.218**	0.233*	0.240**	0.259***	-0.0134
	-0.107	-0.125	-0.014	-0.0985	-0.27
Loss aversion	-0.00825	0.00127	-0.0107	-0.0117	-0.0109
	-0.0101	-0.0115	-0.251	-0.00953	-0.0304
Age	-0.000728	-0.00087	0.000352	-0.000859	-0.00704
	-0.00461	-0.00356	-0.908	-0.00299	-0.00458
Education	-0.00653	-0.00126	-0.00542	-0.00769	0.00277
	-0.0138	-0.0119	-0.633	-0.0113	-0.0184
HH Poverty Score	-0.0045	-0.00541	-0.00499	-0.00520*	0.00987
	-0.00356	-0.00371	-0.101	-0.00303	-0.0127
wheat_rice_income	-0.00410*	-0.00480*	-0.00412**	-0.00483**	-0.00663
	-0.0024	-0.00247	-0.0466	-0.00208	-0.00544
Land Owned Acres	-0.00425	-0.00890**	-0.00453**	-0.00360*	0.00194
	-0.0032	-0.00349	-0.0309	-0.00202	-0.00356
Distance to Ag Ext(KM)	-0.000746	-0.0128	-0.00024	0.000934	-0.0211
	-0.00754	-0.0103	-0.979	-0.0099	-0.0164
Dummy Info from extension	-0.306***	-0.441***	-0.319***	-0.292**	0.133
	-0.105	-0.137	-0.00472	-0.122	-0.209
Year First Known	-0.079	-0.226***	-0.0842**	-0.0718*	-0.171**
	-0.0492	-0.0841	-0.028	-0.0377	-0.0866
Dummy for Haryana	-1.013**	0.545	-0.925**	-0.754*	-0.971
	-0.397	-0.631	-0.0412	-0.424	-1.463
Constant	160.8	455.5***	171.1**	145.9*	344.8**
	-99.06	-169.5	-0.0266	-75.94	-173.5
Observations	432	432	425	408	158

Robust standard errors in parentheses. All other variables used in the main regression used, but not reported in this table.