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Adoption of crop insurance and impact: insights from India

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Abstract Agriculture is inherently a risky enterprise because of its dependence on rainfall. To mitigate risks, farmers diversify crops and enterprises, maintain stabilization account or resort to the sale of assets. Crop insurance is a complementary institutional mechanism that aids farmers to cope with risks better. Considering the importance of crop insurance in risk mitigation, this paper using data from a large-scale farmers' survey we identify the factors that influence farmers' decision to buy crop insurance and subsequently assess its impact on farm income, production expenses and productive investments in agriculture. Farmers' adoption of crop insurance is low— 4.80% kharif season and 3.17% in the rabi season mainly on account of lack of awareness about insurance products. Nevertheless, the probability of adoption of insurance is higher for those who experience higher crop loss and have some formal training in agriculture. The subsidy on premium also positively influences crop insurance uptake decisions. On the other hand, the factors like the lower social status, tenant farming and exposure to deficit-rainfall in the previous year are negatively associated with the decision to insure. The results on the impact of insurance are not conclusive to prove that insured farmer subsumes higher risks compared to the uninsured.

Keywords Crop insurance, Impact, Drivers of adoption

JEL classification G23, Q10, Q12, Q18

1 Introduction

Risks and uncertainties are common in agriculture, as there is a lag between decision-making and realising returns. There are several factors that affect the returns from farming, many of which are beyond the control of farmers (Shashikiran & Umesh 2015). Due to climate change, the frequency of risks in farming has increased. Frequent exposure to risks makes farmer's income less predictable and affects their livelihood security (Birthal et al. 2015).

Farmers follow several ex-ante risk aversion strategies and ex-post risk coping strategies. Crop diversification, staggered sowings, self-stabilization funds, contract farming, are few ways of reducing risk ex-ante. Once the risk is actualised, farmers follow diverse ways to cope with it. Sale of assets, borrowings (formal and non-formal) and governments assistance are the traditional means of ex-post risk management. Many times, these methods fail because of 'covariate nature' of risks. Risks affect almost all farmers of a region, and when many of them try to liquidate their assets, their prices fall. At the same time, due to increased demand, the interest rate on loans from informal sources climbs an upward spiral (Hazell 1992). Government disaster payments, on the other hand, are uncertain and subjected to many 'ifs and buts.'

In the absence of reliable risk coping mechanisms farmers try to avoid risks. They may circumvent risky propositions at the cost of future income (Liu et al. 2013). Resources may be used at sub-optimal levels, as farmers hesitate to invest more in the face of risk.

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Crop insurance can be the instrument as it helps farmers cover the crop loss. However, insurance in agriculture sector is challenging. The insurance markets work perfectly if the underlying risks are independently distributed, risk position of the insured is known, and the insured has no control over the event or the claim. In crop insurance, seldom these conditions are met and result in market failure (Ahsan et al. 1982).

Indian crop insurance schemes, to its credit, are the largest in the world in terms of farmers covered. At the same time, India also has the largest number of uninsured farmers in the world (Mahul & Verma 2010). Many earlier studies have pointed out abysmally low uptake of insurance products by farmers. Considering the importance of the insurance programme to an agrarian economy like India, the reasons for its low popularity needs to be identified. One way of doing it is to characterise those who buy insurance against those who do not. At the same time, it is worth enquiring 'whether the insurance coverage makes farmers less risk-averse'; which is the expected impact of insurance. In this line, the objectives of the study are: (i) to know the factors influencing farmers crop insurance adoption decisions, and (ii) to analyse the impact of insurance on farmer's income, production expenses and investment in agriculture.

2 Data and method

We have used data from "Situational assessment survey of farmers" conducted by National Sample Survey Office (NSSO) in 2012- 2013(GoI 2014a). The data-set includes a sample of 35,200 households spread across 4,529 villages of the states and union territories of India. The data were collected for two major agricultural seasons, namely kharif (2012) and rabi (2012-13) in two separate visits. In the ongoing insurance schemes, each state follows its own subsidy policy and subsidy varies across crops and states. It provides a perfect experimental set up to analyse the effect of government policy on crop insurance coverage.

We collected data on subsidy per hectare of land insured under the National Agricultural Insurance Scheme (NAIS) from the website of the Agricultural Insurance Corporation (http://www.aicofindia.com/AICEng/Pages/BusinessProfileNAIS.aspx). This variable is used as a proxy for subsidy policy. District-wise monthly rainfall data for 2011 were compiled from the India Meteorological Department (IMD). Districts, where actual monsoon rainfall (from June to September) is deficient by 20% or more, are considered as rainfall deficit area in the analysis.

Data from both rabi and kharif seasons was merged to bring it to the household level. The household, which has insured any of the crops in either of the seasons, is considered as an adopter of crop insurance. Subsequently, probit regression with a set of explanatory variables has been employed to identify drivers of adoption of crop insurance. Standard errors are clustered at region level to minimise spatial correlations.

The adoption of crop insurance (Y) is a dichotomous variable; it takes value 1 if the farmer has insured his crop and zero otherwise. Three variants of probit models were employed: These are:

Model 1: $I_i = \sum_{k=1}^{k} \beta_k x_k + e$ without region fixed effects …(1)

Model 2: $I_i = \sum_{k=1}^{k} \beta_k x_k + e$ with agro climatic region fixed effects …(2)

Model 3: $I_i = \sum_{k=1}^{k} \beta_k x_k + e$ with state fixed effects …(3)

The adoption pattern of crop insurance is influenced by agro-climatic factors, crops grown and socio-economic differences across states. This leads to a violation of the important Gauss-Markov assumption of no correlation between the error term and explanatory variables, leading to compromised estimates (Bafumi & Gelman 2006). Therefore, to soak up unobservable across group variability, regressions with two different fixed effects are used (model 2 & 3). In model 2, the states are grouped into 15 agro-climatic regions and used to fix the differences across regions. However, it cannot control for many other factors that vary across states rather than agro-climatic regions, hence; we have used state fixed effects in model 3. These two models help in reducing omitted variable bias. The explanatory variables used in the regression are summarised in table 1.

The impact of crop insurance on investment, credit, crop cultivation expenditure, input use and income

Table 1. Variables used in probit regression

Variable	Unit of measurement	Expected sign
N- dependent variable	Dummy (1 if insured, 0 otherwise)	
Sex	Dummy (1 if male 0 otherwise)	±
Literate-non -formally	Dummy (1 if literate without schooling, 0 otherwise)	+
Literate - primary	Dummy (1 if educated till primary, 0 otherwise)	+
Literate-below secondary	Dummy (1 if educated below secondary, 0 otherwise)	+
Literate-above secondary	Dummy (1 if educated above secondary, 0 otherwise)	+
Training	Dummy (1 if received training in agri, 0 otherwise)	+
Household size	Number of family members	±
ST	Dummy (1 if belong to Scheduled tribe, 0 otherwise)	-
SC	Dummy (1 if belong to Scheduled caste, 0 otherwise)	-
OBC	Dummy (1 if belongs to other backward caste, 0 otherwise)	-
Age	Age of head of household	±
Age^2	Age of head of household (squared)	±
Land	Acres	+
Land posessed^2	Square acres	+
Land leased-in	Acres	+
Agri_primaryincome	Dummy (1 if agriculture is the primary source of income, 0 otherwise)	+
The total value of the output	'000'Rupees/ha	+
Crop loss experience	Dummy (1 if suffered crop loss, 0 otherwise)	+
The proportion of crop loss experienced within the region	Unit less	+
Irrigation	Dummy (1 if some area is under irrigation in either Kharif or rabi, 0 otherwise)	+
Subsidy	Rs/ha	+
Deficit rainfall	Dummy (1 if the district was deficient in monsoon rains last season, 0 otherwise)	+

Source: Authors'

were studied at disaggregated level focusing only rice farmers. Impact on these outcome variables assessed using propensity score matching. In non-experimental studies, it is often difficult to draw the causal inference. Indeed, estimating treatment effect where no experimental methods/designs are used to maintain a control group is a challenge (Dehejia & Wahba 1999). Comparing the treatment group with improper control group may suffer from sample selection bias (Guo et al. 2004; Caliendo & Kopeinig 2005). Matching techniques aim at comparing treatment and control units that are similar with respect to some observable characteristics. Propensity score matching is a non-parametric method which helps to estimate the outcome of treatment on a particular unit if the same unit were not to receive the treatment. It works on the identification assumption that the outcomes are independent of assignment to treatment conditional upon the observable characteristics (Essama-Nssah 2006). The method can be represented by the following equations:

$$Y \perp D \parallel P(Xi) \qquad \ldots(4)$$

Where i is the index of the population under the study and Y is the variable of interest (outcome variable). D represents grouping variable, equals 1 if the household is the adopter of crop insurance (treatment) and zero for non-adopters (control). Thus, the treatment effect for a particular unit it can be expressed as:

$$T_i = E(T_i/D{=}1) = E\ \ (Y_{i1}/D = 1) - (Y_{i0}/D{=}1) \qquad \ldots(5)$$

is unobservable and hence cannot be estimated (Davis et al. 2010). If the identification condition is satisfied, will not differ significantly across treatment and control, we can rewrite the equation (5) as:

$$T_i = E(T_i/D{=}1) = E\ \ (Y_{i1}/D = 1) - (Y_{i0}/D{=}0) \qquad \ldots(6)$$

Following Diaz & Handa (2006) we also compute the bias associated with the estimator as:

$$B = E\ (Y_{i0}/D = 1) - (Y_{i0}/D{=}0) \qquad \ldots(7)$$

All possible variables, which can influence the assignment of treatment, are chosen carefully for computing the propensity score. Common support is ensured using calliper of 0.02. We estimate the effect of insurance using the nearest neighbour method (NN match with 1, 3 and 5 neighbour) of matching with no replacement.

An insurance programme is efficient when it induces farmers to take up more risk, which they would not have taken in the absence of it. As insurance reduces the risk in farming, farmers will assume more financial risks, which are often termed as 'risk balancing' (Liang 2014). It is also hypothesised that farmers will use the resources at profit maximising levels when they are provided with insurance protection. In order to test these hypothesises, five outcome variables have been chosen based on theoretical expectation and review of the literature. These are: debt (formal), debt (informal), cost of production, seed cost, the value of output (gross income) and productive investment in agriculture.

The estimated treatment effect is reliable if the confounders/covariates used for matching are sufficient and a subject in the matched pair has an equal chance of being in the treated group or in control. Rosenbaum bounds are used for the purpose of sensitivity analysis.

3 Adoption of crop insurance

The information on the adoption of crop insurance by farmers is presented in table 2. Only 4.80 and 3.17% is the adoption of crop insurance in kharif and rabi season (without using sampling weights), respectively. Indeed, for India, where agriculture is dominated by small and marginal farms coupled with more area being rainfed, the figures are startling. Even crop wise analysis reveals that the extent of insurance less than 10% except for groundnut, soybean and cotton (table 3). In the two most important food crops in India, rice and wheat, the extent of insurance is less than 5%. For most of the crops the proportion of farmers reporting crop loss is substantial (more than 25% more most crops) and in spite of it, the insurance coverage is low.

Another worrisome fact is that the proportion of non-loanee farmers who have insured their crops are very low. The number for voluntary crop insurance stands at 0.73 and 0.38% respectively for kharif and rabi seasons. Rest are those farmers who have taken crop loan, with which crop insurance is bundled mandatorily. Swain (2014) also finds a significant decline in the share of non-loanee farmers from 11.9% in 2001 to 1.1% in 2011. For a farmers who wishes to insure his crop voluntarily the scheduled commercial or cooperative bank is the intermediary. The banks have no incentive to bring more farmers under the ambit of voluntary insurance as only 4 % of the premium is paid to them as a service charge (Swain 2014). A recent study by Haque & Khan (2017) finds that farmers who own small landholdings, lack irrigation facilities, assets, credit and technical advisory are riskier and suffer more loss. Inadequate drought and insect/disease/animal attack came out as a credible threat and major reason for crop loss. Therefore, the study suggests that insurance could be one possible way to mitigate the loss.

Evidence suggests that the sum insured is very low, not even half of the average value of threshold yield

Table 2. Adoption of crop insurance by farmers

Particulars	Type of insurance	Kharif		Rabi	
		Number	%	Number	%
Insured	Loanee	2,212	4.07	1,335	2.79
	Non- loanee	398	0.73	180	0.38
	Sub total	2,610	4.8	1,515	3.17
Not insured	Not insured	51,749	95.2	46,314	96.83
	Total	54,359	100	47,829	100

Source: Authors' estimates based on data from 'Situational assessment survey of farmers'
Note: The table presents insurance coverage considering crop as a unit of analysis and not farm as a whole.

Table 3. Crop-wise adoption of crop insurance by farmers (%)

Crop	Number of farmers	Insurance coverage (%)	Farmers suffering crop loss (%)	Value of crop (Rs/ha)	Crop loss (Rs/ha)
Rabi					
Rice	4,244	3.9	23.2	50628	19938
Sorghum	534	3.4	63.6	18594	16281
Maize	1,299	3.1	27.8	78344	24197
Wheat	10,956	4.1	29.0	38900	13558
Green gram	2,199	9.6	44.5	30040	19927
Redgram	496	2.8	46.2	31982	26493
Kharif					
Rice	18,388	4.8	28.7	43583	16248
Sorghum	1,679	7.9	49.5	17757	19598
Maize	4,180	4.6	40.0	27692	15923
Green gram	132	8.9	63.6	18359	18440
Redgram	1,239	8.2	40.3	30696	13258
Soybean	857	14.0	50.8	41366	33360
Cotton	1,754	10.4	49.0	32419	16173
Groundnut	429	24.5	14.5	48614	16378

Source: As for table 2.
Note: Crop loss per hectare is calculated as loss per farmer who has suffered loss

implying smaller pay-outs at the event of crop loss (Damodaran 2016). In addition, 87 and 85% of the insured farmers who have also suffered crop losses, report nonreceipt of compensation. Even for farmers who have received the claims, it is not on time (table 4). This highlights the need for improving the triggers in the crop insurance programmes. Cases like this where farmers suffer the loss and yet do not receive any compensation lead to dissatisfaction regarding the operation of the scheme.

High extent of 'basis risk' i.e., insured farmers having suffered crop loss and not given compensation, has its root in the design of schemes. Indian crop insurance schemes operate in 'area approach'. The same rate will be used in the calculation of pay-offs for all the farmers in that area where the risk is actualised. Area based crop insurance is effective only if farmer's yield is correlated with area-yield which is used for calculation of claims (GoI 2014b).

Table 4. Timeliness in settlement of claims (only for voluntary insurers who have reported losses)

Timeliness in Settlement	Kharif		Rabi	
	Number	%	Number	%
In time	15	5.9	8	7.3
Received but delayed	18	7.1	9	8.2
Not received	221	87.0	93	84.6
Total	254	100.0	110	100.0

Source: As for table 2

It is not surprising that the major reason for non-adoption on insurance scheme is the lack of awareness (table 5). More than 70 % of the farmers chose not to insure their crops due to three reasons – not aware, not aware of the existence of the facility and no need. Eric et al. (2004) also report similar observations. The question here why is this apathy towards crop insurance? First, as noted earlier, the market on its own will not supply enough insurance as the preconditions for perfect competition cease to exist in the crop insurance market (Ahsan et al. 1982). Second, the banks, which act as a financial intermediary, have little incentives to promote insurance products. Third, the extent of basis risk is high due to poor triggers coupled with small sum insured.

To understand the drivers of crop insurance uptake decision, we have used three probit models with minor

Table 5. Reasons for not insuring the crop (in %)

Crop	Not aware	Not aware aboutthe existence of the facility	Not interested	No need	Others
Rice	43.2	18.5	15.2	5.2	15.5
Wheat	20.8	13.1	19.1	5.8	15.8
Maize	46.4	18.6	12.2	4.7	16.7
Cotton	39.6	14	17.3	2.6	25.4
Red gram	41.1	16.3	14.7	3.3	24.6
Black gram	52.2	19.2	11.8	3.8	13
Soybean	44.8	16	17.6	2.8	18.8

Source: As for table 2.

modifications to accommodate spatial variability. The results are depicted in table 6. Out of four education variables, most of the variables are positive and statistically significant when the region fix effects are included. Educated farmers are more likely to buy an insurance product. The variable for training in agriculture, which is also a proxy for exposure to extension services, is also positive and statistically significant.

Particularly, for a financial tool like insurance, which is not an investment to increase income, instead, to cope with risk better, the role of training and education is important. Insurance procedures are complicated in a sense that terms such as sum insured, and indemnity levels are difficult to understand by farmers. (Eric et al. 2004). As we know, complexities are negatively correlated with the rate of adoption of any new technology. Hence, both education and extension (training in agriculture) are crucial in creating awareness about the insurance schemes.

Higher the holding size, higher is the probability of taking insurance cover as indicated by the positive and significant coefficient for the land variable. With the increase in holding size, the level of marketable securities also increases and greater the chance that farmers go for formal credit source, with which the insurance product is bundled. Nevertheless, large farmers are less likely to take up insurance. Large farmers usually diversify crops as well as an enterprise to mitigate the risks rather than depending on insurance. Nair (2010) has also reported similar findings that 60% farmers who insure their crops are small and medium.

The variable for subsidy on premium is not statistically significant in the first two models. However, when the state fixed effects are included, the coefficient on subsidy, as expected, turns positive and significant. The subsidy is important for many obvious reasons. The subsidy will increase the depth of insurance cover in terms of sum insured. Resources available with the farmers are limited, and at the start of agricultural season cash requirement is also high and, in many cases, farmers cannot afford to pay high premiums. Subsidising premiums will go a long way in increasing the enrolment of farmers to make schemes sustainable (Liang 2014; Babcock 2015).

Crop loss experience is also positive in our model, reinstating hypothesis that exposure to risk makes farmers risk-averse and induces them to buy insurance coverage. Dummy for agriculture as a primary source of income is positive too. Greater the dependence of farmer on agriculture, higher is the probability that they want to minimise the risk associated with it and hence insure their crops. However, on the other hand, dummy for deficit rainfall is found to be negatively influencing the decision to insure crops. Farmers, in areas where droughts are common, depends more on traditional and safer methods of risk aversion like intercropping, crop diversification, drought-resistant varieties, etc. rather than on insurance. Results of earlier studies also support our findings that drought is negatively associated with the decision to insure the crop (Hazell 1992; Eric et al. 2004).

If the farmer belongs to lower social caste (SC/ST/OBC), less is the probability that he goes for insurance as shown by the negative sign of the respective variables. For the majority of the farmers who are not in the general category of caste, resource endowments are small, so as the access to institutional credit (Kumar

Table 6. Correlates of crop insurance adoption: probit model

Variable	Model 1	Model 2	Model 3
Sex	0.1208*	0.0465	0.0307
	(-0.0725)	(-0.0722)	(-0.0688)
Literate-non formally	0.1998	0.2905**	0.3219**
	(-0.125)	(-0.1302)	(-0.1261)
Literate -primary	-0.0259	-0.0081	0.0165
	(-0.0709)	(-0.0555)	(-0.0497)
Literate-below secondary	0.0198	0.1120**	0.1398***
	(-0.0567)	(-0.0486)	(-0.0435)
Literate-above secondary	-0.0217	0.1189*	0.1454**
	(-0.0778)	(-0.0661)	(-0.0614)
Training	0.1986**	0.1900**	0.2290***
	(-0.0972)	(-0.0822)	(-0.0855)
Household size	-0.0145*	0.001	0.0056
	(-0.0083)	(-0.0052)	(-0.005)
ST	-0.2829**	-0.5140***	-0.5702***
	(-0.1149)	(-0.1)	(-0.097)
SC	-0.1826**	-0.3023***	-0.3235***
	(-0.0904)	(-0.0872)	(-0.0876)
OBC	-0.0146	-0.1370**	-0.1557***
	(-0.0795)	(-0.0595)	(-0.0597)
Age	0.0043	0.0042	0.0041
	(-0.0062)	(-0.0062)	(-0.0063)
Age^2	-0.0001	0	0
	(-0.0001)	(-0.0001)	(-0.0001)
Land	0.1731***	0.1380***	0.1319***
	(-0.0208)	(-0.0183)	(-0.0178)
$Land^2$	-0.0044***	-0.0038***	-0.0034***
	(-0.0011)	(-0.001)	(-0.0009)
Land leased-in	-0.0390**	-0.0442**	-0.0605***
	(-0.0198)	(-0.0186)	(-0.0201)
Agriculture- primary income	0.2722***	0.2462***	0.2440***
	(-0.0659)	(-0.0583)	(-0.0532)
The total value of the output	-0.0001	0.0008**	0.0008**
	(-0.0004)	(-0.0003)	(-0.0003)
Crop loss experience	0.1787***	0.1931***	0.2006***
	(-0.0567)	(-0.0589)	(-0.0601)
Proportion of crop loss experienced within the region	0.3972	-0.3252	0.2114
	(-0.285)	(-0.4077)	(-0.4081)
Subsidy	-0.0001	0.0012	0.1723***
	(-0.0003)	(-0.0014)	(-0.0353)
Irrigation	0.0056	0.0189	0.0203
	(-0.0836)	(-0.0631)	(-0.0615)
Deficit rainfall	-0.4383***	-0.2563***	-0.2685***
	(-0.0939)	(-0.092)	(-0.0906)
Constant	-2.2108***	-3.2402***	-11.0571***
	(-0.2886)	(-0.4384)	(-1.8171)
Number of observations	30599	30110	30353

Source: Authors' estimate

Notes: Model 1: No region fixed effects; Model 2: Agro- climatic region fixed effects; Model 3: State fixed effects. Standard errors are in parentheses and are clustered at the region, and *, **, *** represents significance at 10, 5 and 1% level, respectively

Table 7. Impact of crop insurance on risk attitude and income

Variable	Overall sample		Voluntary insurers only	
	Difference	t-stat	Difference	t-stat
Debt (Rs /household)	91108	5.27	-17968	-0.47
Total cost of production (Rs/farm)	160933	5.20	-343030	-0.70
Seed cost (Rs/farm)	5322	3.55	643	1.48
Debt from Informal source (Rs /household)	49038	5.36	-10898	-0.57
Value of crop output (Rs/farm)	7553	0.98	5992	0.74
Productive investment in agriculture (Rs /household for six month)	101811	0.47	27142	0.89

Source: Authors' estimate
Note: ATT= Average treatment effect on treated. Matching method: Nearest neighbour with calliper

et al. 2015; Birthal et al. 2017). Tenancy is also found to have a negative influence on the adoption of insurance. The farmer, who has more leased-in land, is less likely to buy an insurance product. Under the current scheme, leased-in lands can be brought under the ambit of insurance cover by producing proof showing crop sharing/tenancy arrangements (Singh 2010). In India, the majority of the crop sharing/ tenancy agreements are through word of mouth and producing such documents is difficult. Another possible reason could be that tenancy is a coping mechanism by itself. It helps in sharing of risks both for the landlord and tenant (Mishra 2008).

4 Impact of crop insurance on farmer's risk attitude and income

Propensity score matching has been employed using the psmatch2 command of Stata after ensuring that covariates are balanced within all the panels. We have used nearest neighbour calliper method (with a calliper of 0.02) to ensure common support (Guo et al. 2004). Since the control group is large, we could find good matches within the specified calliper to more than 99% of the treated observations. Bias is also very less and not significant statistically for any of the covariate included in the model. Results are presented in table 7.

The variables like debt, input costs, investment and value of the output of the insured farmers are found significantly higher than the control group validating the risk balancing behaviour of farmers. Insured farmers transfer risk to the insurer and offset it by seeking higher risk in farming which can increase overall welfare. Even the results of sensitivity using Rosenbam bounds indicate consistent and stable estimates. However, in India, insurance is bundled with credit (mandatory insurance coverage for farmers who availed short-term credit). Hence, the observed impact of insurance can also be due to endogeneity between insurance and credit. As a check, we have used propensity score matching on voluntary insurers (for whom insurance is a choice). Treatment effect on none of the outcome variables is significant, in contrast to the earlier result. Therefore, the earlier results may be due to the simultaneous effect of credit and insurance. Hence, we conclude that no reliable empirical evidence is found to show that insured farmers take more risk in farming.

From our propensity score matching estimates, we do not find any evidence of crop insurance on outcome variables. In addition, we also highlighted some limitations of the study. Most of the variables included in the probit model are endogenous except deficit rainfall and subsidy. The models can best estimate the correlates but do not reveal any causal relationship. Since the data doesn't include information on the sum insured, factors determining the depth of insurance coverage couldn't be analysed. Matching technique employed here do have inbuilt disadvantages, as we cannot control for many unobservable characteristics which might influence the allotment and impact of treatment.

5 Conclusion and policy implications

The study brings out that the adoption of crop insurance by farmers is very poor with only 4.80 and 3.17 % of the sample farmers insuring their crops in kharif and rabi season, respectively. For most of the insured farmers, insurance was bundled with credit and the extent of voluntary insurance is very low (0.73 and 0.38 % in kharif and rabi respectively). We found that educated farmers with better extension contact are more likely to insure their crops. Land holding size and subsidy on premium was also found to increase the probability of farmers to adopt crop insurance. Farmers belonging to backward castes and tenants are less likely to purchase crop insurance. Impact of crop insurance purchase on the value of output, crop production expenses and investments of rice growers are inconclusive from the study. Based on the results, it is clear that the extension mechanism needs to play a pivotal role in creating awareness about crop insurance. For a financial product like insurance, awareness creation plays a pivotal role in achieving large-scale adoption. 'Basis risk' needs to be reduced by way of improving the triggers of crop loss estimation. Redesigning of crop insurance programme should consider the issues of inclusivity with respect to tenant farmers and small farmers.

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Appendix 1: Summary of variables in the control and treatment groups

Variable	Unit	n=0		n=1	
		Mean	Std. Dev	Mean	Std. Dev
Sex	Dummy (1 if insured, 0 otherwise)	0.92	0.27	0.95	0.23
Literate-non formally	Dummy (1 if male 0 otherwise)	0.01	0.1	0.01	0.11
Literate _primary	Dummy (1 if educated till primary, 0 otherwise)	0.13	0.34	0.12	0.32
Literate-below secondary	Dummy (1 if educated below secondary, 0 otherwise)	0.41	0.49	0.43	0.5
Literate-above secondary	Dummy (1 if educated above secondary, 0 otherwise)	0.12	0.32	0.13	0.34
Training	Dummy (1 if received training in agriculture, 0 otherwise)	0.04	0.19	0.06	0.24
Household size	Number of family members	5.43	2.73	5.47	2.76
ST	Dummy (1 if belong to Scheduled tribe, 0 otherwise)	0.2	0.4	0.1	0.31
SC	Dummy (1 if belong to Scheduled caste, 0 otherwise)	0.12	0.32	0.08	0.28
OBC	Dummy (1 if belongs to OBC, 0 otherwise)	0.39	0.49	0.49	0.5
Age	Age of head of household	51.04	13.43	51.62	13.18
Age2	Age of head of household (squared)	2784.97	1426.45	2838.63	1415.23
Land	Acres	1.55	1.77	2.65	2.82
Land posessed2	Square acres	5.54	40.67	14.95	68.26
Land leased-in	Acres	0.17	0.8	0.28	1.26
Agri_primaryincome	Dummy (1 if agriculture is the primary source of income, 0 otherwise)	0.7	0.46	0.83	0.38
Total value of output	‘000’Rupees/ha	19.33	44.21	31.7	64.1
Crop loss experience	Dummy (1 if suffered crop loss, 0 otherwise)	0.46	0.5	0.63	0.48
Proportion of crop loss experience within region	Unit less	0.46	0.23	0.55	0.22
Irrigation	Dummy (1 if some area is under irrigation in either Kharif or rabi, 0 otherwise)	189.44	273.13	179.62	269.5
Subsidy	Rs/ha	0.67	0.47	0.71	0.45
Drought	Dummy (1 if district received deficient monsoon rains last season, 0 otherwise)	0.32	0.46	0.14	0.34

Appendix 2: Crop insurance: reasons for non-adoption/dis-adoption (in per cent)

Crop	Not aware	Not aware of the existence of the facility	Not interested	No need	Facility not available	Lack of resources	Not satisfied with terms and conditions	Nearest bank at a long distance	Complex procedures	Delay in settlement
Rice	43.2	18.5	15.2	5.2	6.2	3.7	1.7	0.3	2.7	0.9
Maize	46.4	18.6	12.2	4.7	7.1	3.9	3.4	0.1	1.7	0.5
Cotton	39.6	14	17.3	2.6	10	7.9	4.6	0.3	1.5	1.1
Pearl millet	51.2	17.5	14.4	5.6	4.2	4.1	1.2	0.1	0.6	0.5
Soybean	44.8	16	17.6	2.8	4	6	4.6	0.4	3	0.3
Coconut	33.6	11.4	24.4	13.1	5.6	2	3.2	0.3	2	0.1
Sorghum	43.5	12.9	15.4	4.2	5.7	4.9	7.9	0.4	1	0.9
Sugarcane	38.8	21.1	13.1	9.3	6.7	3.6	2.2	0	3.3	0.5
Red gram	41.1	16.3	14.7	3.3	9.3	6	5.5	0.5	1.5	0.7
Black gram	52.2	19.2	11.8	3.8	6.2	1.5	1.7	0	0.3	1.2
Potato	40.9	9.5	9.4	4.8	17.1	3.3	5	0.1	6.3	1.4
Groundnut	48.9	17.9	15.8	3.5	4.9	2.5	2.9	0	1	0.2
Ragi	45.1	12.2	11.6	5.3	18.5	2.3	4	0.3	0.1	0.2
Green gram	48	14.5	19.1	1.1	4.6	5	2.1	0.8	0.7	0.9
Jute	64.2	12.4	10.2	4	3.6	0.4	0	0	0.9	0.1
Sesamum	48	23.7	12.2	2	1.9	7.9	1.2	0	0	2
Onion	25.8	8.3	12.7	3.2	26.5	0.9	16.7	0.2	0.3	0.3
Rapeseed	35.3	9.9	12.6	7	3.4	3.2	0.3	0	24.3	0
Wheat	20.8	13.1	19.1	5.8	15.8	8	9.7	0	1.2	2.2
Chick pea	30.1	15.3	23.5	2.7	4.6	7.9	14.6	0	1.1	0.3