Agricultural Economics Research Review 2022, 35 (Conference Number), 109-116
DOI: 10.5958/0974-0279.2022.00023.4

Analysing the effectiveness of crop insurance scheme as an adaptive strategy against climate change in Himachal Pradesh

Deepali Chadha[1]* and S K Srivastava

Department of Agricultural Economics, G.B. Pant University of Agriculture and Technology, Pantnagar, Uttarakhand 263145, India

*Corresponding author: deepalichadha6989@gmail.com

Abstract Using the data from different altitudes of Himachal Pradesh, present study analyses the effectiveness of crop insurance scheme, which is not only restricted to simple comparison of costs and returns, but also incorporates the application of standard treatment effect model to analyse the selection bias, if any, prevalent in the model. The findings revealed that crop insurance couldn't bring much difference in the income of farmers. Only, little difference of 2.5% has been observed in tomato, mainly due to the credit that has helped them to invest more in quality inputs and thus, bringing higher returns. The study suggests for an effective improvement in the system to safeguard the interests of the farmers.

Keywords Crop insurance, insured, non-insured, treatment

JEL codes Q12, Q18, Q58

Climate change is speeding up, and this, together with rising income levels and population, poses a challenge to global food security. India has reasons to be concerned about climate change (Garg et al. 2009) because a large portion of its population relies on different climate-sensitive sectors. Indian agriculture is one of the most vulnerable and exposed to climate change (Birthal and Hazrana 2019; Datta, Behera, and Rahut 2022), owing to a lack of adaptive capacity to deal with the consequences of the climate change (Birthal et al. 2014). Climate change impact combined with other risk factors has created a crisis situation in Indian agriculture (Kanwal, Sirohi, and Chand 2022; Nadkarni 2022); as a result farmers' suicides are being reported in most of the states. This necessitates the need for a broad spectrum of policy responses and strategies at different levels.

Crop insurance is one among the anticipatory adaptation measures proven worldwide as an effective institutional mechanism to overcome the adverse impacts of climate variability. It helps in stabilization of farm production and income through promoting technology, encouraging investment, and increasing credit flow in the agriculture sector of the farming community (Jain and Dharmaraja 2018). Although, crop insurance, in general, has not been so successful in India (Gulati, Terway, and Hussain 2018) and is mostly prevalent in the southern states of the country. However, the northern regions of the country have a very low enrolment ratio under the scheme. North Himalayan ecosystems are among the most vulnerable to climate change around the world. They have rugged topography along with the limited livelihood choices, financial constraints, limited land for cultivation and are highly susceptible to the natural disasters (Negi et al. 2017; Tewari, Verma, and Gadow 2017). This calls for an effective institutional mechanism that can safeguard the interests of the farmers in these regions.

Various crop insurance studies conducted in India have brought inconsistent outcomes, for instance, positive impact has been witnessed in the state of Andhra Pradesh (Kumar and Babu 2021), Tamil Nadu (Varadan and Kumar 2012); while it has failed to meet the expectations in Gujarat (Bahinipati 2022). However, no such attempt has been made too far to assess the efficiency of crop insurance in one of the most susceptible states of Himachal Pradesh. The outcomes of a simple comparison between insured and non-insured farmers may be biased due to the influence of several unobservable factors (Kishore 2019). Keeping this into consideration, the present study analyses the effectiveness of crop insurance scheme across different altitudes of the Western Himalayan ecosystem by keeping into consideration the selection bias.

Data and descriptive statistics

Study area

The present study has been conducted in Himachal Pradesh state of India. Being a part of Himalayan mountain ecosystem, the state is especially vulnerable to climate change, and all its attendant adverse effects (Bisht et al. 2018). The state is located at the foothills of the western Himalayas, with over 89% of the population living in rural areas (Statistical Abstract of Himachal Pradesh 2019-20) where people have comparatively lower rates of technology adoption and modernization. Agriculture, which employs roughly 70% of the working population and accounts for nearly 22% of the total state domestic product, is the primary source of income for communities residing in the state (State Performance Report 2020-21). Small and marginal farmers own 88.86% of the total land holdings, while rainfed agriculture accounts for nearly 80% of the total cultivated area in the state (Himachal Pradesh Economic Survey, 2020-21). Extreme weather conditions along with inability of the people to cope up with the situation renders the state as one of most vulnerable ecosystems.

Being primarily an agrarian state, which is highly prone to natural disasters; Himachal Pradesh needs a robust crop insurance system. However, the number of farmers covered under crop insurance is comparatively very low in the state. According to the report of Comptroller and Auditor General of India (CAG), 2017, less than 2% of farmers in Himachal Pradesh were covered under the crop insurance scheme during the period from 2014 to 2017. Moreover, farmers benefited under PMFBY scheme ranged between 1.64 and 15.92% in *Kharif* season and between 0.80 and 36.40% in *Rabi* season of the total farmers in different districts. Thus, in order to address the various issues which are hindering the adoption and successful implementation of the schemes in the state, it is imperative to analyse the effectiveness of crop insurance scheme in Himachal Pradesh.

Sampling

Multistage stratified random sampling has been done to select the farmers for the collection of primary data. Presently, two crop insurance schemes viz., Pradhan Mantri Fasal Bima Yojana (PMFBY) and Restructured Weather Based Crop Insurance Scheme (RWBCIS) are operative in the state. Both the schemes cover different kind of crops in the state. PMFBY covers the major foodgrain crops while; RWBCIS covers the major fruit and vegetable crops. Since, the present study is concerned with one agricultural year; therefore, only vegetable crops, covered under RWBCIS, have been taken into account. The present research aims to study the usefulness of crop insurance scheme as an adaptive measure against the ill-effects of climate change. As, altitude of a place governs the climate of a region, therefore, firstly the districts where all the three altitude ranges (low hills (upto 1000 m amsl), mid hills (1001-1500 m amsl) and high hills (1500 - 2500 m amsl)) exist are selected. Among them, those districts which are having maximum number of farmers covered under the crop insurance are selected.

Overall, a total of four districts i.e. two districts under each crop insurance scheme have been selected. Kangra and Mandi districts have been selected to represent Pradhan Mantri Fasal Bima Yojana (PMFBY), as these districts together shared more than 80% of the insured farmers, among the districts possessing all the three altitudes. Similarly, under Restructured Weather Based Crop Insurance Scheme (RWBCIS), Solan and Sirmour districts have been selected as both of them were collectively covering more than 80% of the total insured farmers under the scheme and possess wide elevation range across the districts.

Selection of farm households

All the blocks of selected districts have been classified into three strata based on major portion under the above mentioned three altitudes. Thereafter, one block has been selected randomly from each stratum of each selected district, making up a total of 12 blocks from 4 districts. From each block, 3 villages have been selected randomly. Out of each village, 5 insured and 5 non-insured farmers have been selected randomly, thus, a

Table 1 Crop-wise coverage of farmers under different crop insurance schemes in Himachal Pradesh (2018-19)

Pradhan Mantri Fasal Bima Yojana (PMFBY)			Restructured Weather Based Crop Insurance Scheme (RWBCIS)		
Crops	Number of farmers enrolled	Percentage to total	Crops	Number of farmers enrolled	Percentage to total
Wheat	86823	49.86	Tomato	9540	79.40
Maize	70710	40.60			
Total	174149	100	Total	12015	100

Source Department of Agriculture, Shimla, Himachal Pradesh (2020-21)

total of 30 farmers have been selected from each of the 12 blocks selected from 4 districts. The total sample comprises of 360 farmers (180 insured and 180 non-insured farmers).

Selection of crops

In order to assess the effectiveness of crop insurance scheme, major insured crops of the study area under each scheme have been selected. On the basis of number of farmers covered under the scheme; tomato crop has been selected under RWBCIS while, wheat and maize have been selected under PMFBY (Table 1).

Table 1 Crop-wise coverage of farmers under different crop insurance schemes in Himachal Pradesh (2018-19)

Descriptive statistics

In order to assess the effectiveness of crop insurance scheme, the cost of and returns from the major insured crops have been compared with the non-insured crops using cost concepts given by Commission for Agricultural Cost and Prices (CACP) as Cost A_1, Cost A_2, Cost B_1, Cost B_2, Cost C_1, Cost C_2, Cost C_2^* and Cost C_3.

- Cost A_1 : It includes :

1. Value of hired human labour
2. Value of hired and owned bullock labour
3. Value of hired and owned machine power
4. Value of seed
5. Value of manures and fertilizers
6. Value of mulch
7. Irrigation charges
8. Expenses on plant protection chemicals
9. Depreciation
10. Land revenue
11. Interest on working capital
12. Insurance premium
13. Miscellaneous expenses

- Cost A_2 : Cost A_1 + rent paid for leased-in land, if any.
- Cost B_1 : Cost A_1 + imputed value of interest on owned fixed capital (excluding land).
- Cost B_2 : Cost B_1 + rental value of owned land (net of land revenue) + rent paid for leased-in land.
- Cost C_1 : Cost B_1 + imputed value of family labour.
- Cost C_2 : Cost B_2 + imputed value of family labour.
- Cost C_2^* : estimated by taking into account value of labour at statutory minimum wage rate or actual wage rate, whichever is higher.
- Cost C_3 : Cost C_2^* + 10% of cost C_2^* as management cost.

The net returns computed at Cost C3 and yield of selected crops grown on insured farms are compared with that of non-insured farms and the difference between the two is examined statistically using t-test.

Empirical strategy

Differences in the net income between the insured and non-insured farmers cannot be attributed wholly to the adoption of crop insurance scheme. It may be due to a variety of unobservable factors (such as better farming experience, management skills etc.) that could contribute to a difference in the profit margins as well. Hence, a simple comparison of the net income may be biased and therefore, a standard treatment effects model has been used to correct this bias. In a regression framework, the treatment effects model is given by:

$$R_i = a + bC_i + cX_i + \mu_i \quad (1)$$

Where, R_i is the net revenue of i^{th} farmer for respective crop, C_i is dummy variable taking the value 1 if one adopts crop insurance and 0 otherwise, X_i is vector of the variables believed to affect the net income and μ_i is zero mean random variable. An OLS estimate of equation (1) is likely to be biased because of the effects of unobservable factors. Hence, two-stage Heckman procedure is used to correct for the bias from the endogeneity of right hand side variables. In the first stage, following adoption equation is considered:

$$C_i = \gamma_1 + \gamma_2 Z_i + \mu_i \quad (2)$$

Where, C_i is a binary variable (1 for adopters of crop insurance and 0 for non-adopters) and Z_i is a vector of explanatory variables influencing the adoption. Variables in Z_i will overlap with variables in X_i. Identification requires that there should be at least one variable in Z_i that is not in X_i. If this condition is met, the predicted value from equation (2) can be used as instrument for C_i in the second stage of the model i.e. regression equation (1). Thus, from equation (2), inverse Mills ratio (IMR) is estimated and has been used as an instrument in equation (1) which would yield a consistent estimate of b.

Results and discussion

Comparison of costs and returns from selected crops

The input-use pattern and returns realized from selected crops have been worked out separately for insured and non-insured farmers (Table 2). The above results conclude that not much difference has been witnessed between the proportional spending of insured and non-insured farmers. However, insured farmers spend more on farm inputs while non-insured farmers spend more on labour costs. Thus, they are found to realize comparatively more returns than the non-insured farmers. Overall comparison for all the three crops have revealed that comparatively more returns have been realized for the insured farmers in all the three cases. The difference in the yield of insured and non-insured farmers is found to be significant in case of maize and tomato crops, whereas, it is insignificant for the wheat crop. However, difference in the net returns (at cost C3) of the insured and non-insured farmers is insignificant for maize and wheat crop, while it is observed to be significant for the tomato growers. Further, it has been observed during the survey that majority of the insured farms were of large size as compared to the non-insured farms, while most of the insured farmers were loanee farmers, i.e. those who have taken crop loans. This may conclude that by one or the other way; insurance has benefitted the farmers. Overall, insured farmers invest comparatively more on high valued inputs to increase production, while non-insured farmers rely more on labour.

Treatment effect model for correcting the bias

A simple comparison of average returns between the insured and non-insured farmers could be biased due to the presence of variety of other unobservable factors (such as better farming experience and management skills, etc.). Thus, to consider this bias, standard treatment effects model have been used.

Factors influencing the adoption of crop insurance scheme

First stage of the model corresponding to the equation 2, involving the estimation of probit model to identify the factors that influenced the farmer's decision to participate in crop insurance scheme for all the selected crops is given in Table 3. The results indicate that probability of adoption of crop insurance scheme is higher for those who are KCC holders and have availed crop loan. This is due to the fact that till *Kharif*, 2020; it was mandatory for the loanee farmers to get compulsory insurance.

Besides this, size of the land holding and farming experience of the respondent also have a positive influence on the adoption of crop insurance scheme. The second stage of this approach involves a standard treatment effects model using predicted probabilities from the probit model as an instrumental variable, with net revenue per hectare from crop cultivation as the dependent variable.

After having accounted for the selection bias, effect of crop insurance on net income of the farmers has been

Table 2 Comparative analysis of costs and returns from selected insured and non-insured crops (2019-20)

Particulars	Wheat				Maize				Tomato			
	Insured		Non-insured		Insured		Non-insured		Insured		Non-insured	
	Cost	% of total	Cost	% of total	Cost	% of total	Cost	% of total	Cost	% of total	Cost	% of total
Variable cost												
Human labour (Hired)	1313	5.58	1361	5.75	707	3.89	1100	5.98	5273	8.54	5332	8.71
Human labour (Owned)	3063	13.03	3175	13.41	2357	12.97	2568	13.96	19319	31.29	19508	31.85
Machine labour	6795	28.91	6878	29.05	5705	31.40	5589	30.39	7817	12.66	7923	12.94
Seed	2228	9.48	2181	9.21	2491	13.71	2184	11.87	11884	19.25	11272	18.41
Manures and fertilizers	6470	27.53	6386	26.97	4605	25.35	4583	24.91	8023	13.00	7838	12.80
Plant Protection Chemicals	2311	9.83	2364	9.98	1201	6.61	1265	6.88	4974	8.06	4970	8.12
Miscellaneous	859	3.65	868	3.66	739	4.07	744	4.05	3479	5.63	3447	5.63
Interest on Working Capital	466	1.98	468	1.97	360	1.98	361	1.96	967	1.57	952	1.55
Sub-total	23504	100	23682	100	18166	100.00	18394	100.00	61736	100.00	61242	100.00
Fixed cost												
Insurance premium	450	3.76	0	0.00	600	5.02	0	0.00	5000	34.64	0	0.00
Land revenue	31	0.26	31	0.28	31	0.26	31	0.28	31	0.22	31	0.35
Rental value of owned land	7477	62.55	7422	67.49	7471	62.53	7458	67.36	5324	36.88	5145	58.41
Depreciation	2196	18.37	1936	17.61	2240	18.75	2124	19.18	2479	17.18	2159	24.51
Interest on fixed capital	1799	15.05	1608	14.62	1605	13.44	1459	13.17	1600	11.08	1474	16.73
Sub-total	11954	100	10997	100	11948	100	11072	100	14434	100	8808	100
Total cost at Cost C3	35781		34994		30383		29729		76900		70719	
Yield of main product (qt/ha)	31.34		30.90		28.88		27.71		298.75		294.01	
Yield of by-product (qt/ha)	43.24		42.64		49.09		47.77		0		0	
Price of main-product (Rs/qt)	1975		1975		2000		2000		1162.85		1157.77	
Price of by-product (Rs/qt)	500		500		100		100		0		0	
Gross returns (Rs/ha)	83520		82344		62671		60204		347401		340401	
Cost of production at cost C3(Rs/qt)	846		839		970		988		255		238	
Net Returns (Rs./ha) over Cost C3	47739		47350		32288		30475		270501		269682	

Note The difference between the yield of insured and non-insured farmers is statistically significant at 5% for maize and tomato crops, while difference between the net returns at Cost C3 is significant only for tomato crop)

Table 3 Probit estimates for determinants of adoption of crop insurance for selected crops

Dependent variable: Adoption of crop insurance scheme (Yes=1; No=0)

Crops	Wheat		Maize		Tomato	
Independent variables	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Age of the respondent (years)	-0.008	-0.002	-0.020***	-0.004	-0.005	-0.001
	(0.013)	(0.003)	(0.014)	(0.003)	(0.022)	(0.004)
Total owned land holding (hectares)	0.135***	0.028***	0.147*	0.030*	0.262*	0.045*
	(0.025)	(0.004)	(0.026)	(0.005)	(0.056)	(0.008)
Years of education	0.172**	0.035***	0.164*	0.034*	0.157	0.027
	(0.023)	(0.003)	(0.023)	(0.004)	(0.032)	(0.004)
Farming experience (years)	0.106***	0.022**	0.105*	0.022*	0.115**	0.020*
	(0.015)	(0.002)	(0.016)	(0.003)	(0.025)	(0.004)
Other income source dummy (yes=1; no=0)	-0.222	-0.045	-0.278	-0.058	-0.292	-0.050
	(0.226)	(0.046)	(0.229)	(0.047)	(0.311)	(0.053)
KCC holder dummy (yes=1; no=0)	0.767***	0.157***	0.688**	0.143**	0.224*	0.038***
	(0.291)	(0.058)	(0.293)	(0.060)	(0.420)	(0.072)
Constant	-5.103		-4.304		-4.946*	
	(0.683)		(0.638)		(0.927)	
Number of observations	307	295	195			
LR chi^2	200.5	188.85	149.98			
Prob>chi^2	0.0008	0.000	0.0000			

Note Figures in parentheses are standard errors; *, ** and *** indicate significance at the 1% , 5% and 10 %, significantly.

Table 4 Results of the outcome equation for the selected crops

Dependent variable: Net returns from wheat cultivation (Rs/hectare)

Crops (→) Independent variables	Wheat Coefficient	Maize Coefficient	Tomato Coefficient
Total owned land holding (hectares)	0.0003*	0.0037***	0.0014***
	(0.0013)	(0.0011)	(0.0024)
Farming experience (years)	0.0010**	0.0008*	0.0009*
	(0.0007)	(0.0005)	(0.0010)
Family size (Number of family members	0.0025	-0.0017**	-0.0102*
	(0.0038)	(0.0031)	(0.0061)
Major occupation dummy (agriculture=1, otherwise=0)	-0.0281	0.0048	-0.0161
	(0.0114)	(0.0093)	(0.0168)
Insurance dummy (adopters = 1, non-adopters = 0)	0.0044	0.0199	0.0255***
	(0.0126)	(0.0099)	(0.0193)
Inverse Mills ratio (IMR)	0.0033	-0.0031	0.0113**
	(0.0101)	(0.0082)	(0.0137)
Constant	4.616***	4.524***	5.386*
	(0.0378)	(0.0296)	(0.0543)
Number of observations	307	295	195
Prob>F	0.0076	0.0005	0.0003
R-squared	0.199	0.245	0.2341

Note Figures in parentheses are standard errors; *, ** and *** indicate significance at the 1%, 5% and 10 %, significantly.

estimated for all the selected crops (Table 4). The results of the outcome model suggest that Inverse Mills Ratio (IMR) is statistically significant only in the case of tomato crop, thus, implying that selection bias was prevalent in the model and has been corrected. Further, adoption of crop insurance positively influences the net returns from tomato cultivation i.e. it increases the net returns of tomato growers by 2.5%. However, size of the land holding and farming experience with the farmer are positively related with the net returns of all the selected crops, irrespective of their enrolment under crop insurance scheme.

Conclusions

Himachal Pradesh, being highly prone to natural disasters, needs an effective crop insurance system. However, besides having a low enrolment ratio in the state, the benefits availed from crop insurance are also below the mark. Findings of the study have shown that being a KCC holder has been identified as the most important variable influencing the adoption of crop insurance scheme, mainly due to the earlier provision of compulsory registration of the loanee farmers. Moreover, crop insurance led to a marginal increase of 2.5% in the net returns of tomato crop, while an insignificant impact has been witnessed in case of wheat and maize crops. Overall, the results indicate towards the inefficiency of crop insurance scheme in the state, thus, necessitating the need of government intervention in order to improve its effectiveness, particularly in north Himalayan states, which are under the ultimate risk of climatic vulnerability.

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