
# Crop Insurance and Crop Productivity: Evidence from Rice Farmers in Eastern India

by Anjani Kumar, Sunil Saroj, and Ashok K. Mishra

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## Abstract

The paper explores the spread of crop insurance in India and analyzes the factors affecting the demand for crop insurance. The study also assesses the impact of crop insurance on the rice yields of smallholder rice producers. Using data from a large farm-level survey from eastern India, the study tests for robustness of the findings after controlling for other covariates and endogeneity, using propensity score matching, coarsened exact matching, and endogenous switching regression models. Results indicate a positive and significant impact of crop insurance on rice yields.

**Keywords:** Crop insurance, rice yield, farm size, India, food security, treatment effects

**JEL Codes:** O13; Q14; Q18

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# 1. Introduction

Farming is a risky venture and its outcomes are subject to variations in weather and market forces. Climate change is causing increasingly large weather variations and is likely to have heterogeneous impacts across geographical regions (Lobell et al. 2008; Dell, Jones, Olken 2008). Countries in South Asia and southern Africa are likely to suffer more from climate change and these changes are likely to have an impact on both the production and yield of major crops such as rice and maize. The risk and uncertainty in production and crop yield are likely to impact not only the food security of the nation (Wheeler and von Braun 2013) but is also expected to have a direct impact on income and poverty among rural populations in general and farming households in particular (Barnwal and Kotani 2013). The authors note that rural livelihoods are under threat of increased vulnerabilities in food security.

Given this background, it is vital to understand the instability in production and crop yields and the effectiveness of adaptation strategies on food security. In a recent study, Ray et al. (2015) found that India is among the countries with the highest coefficient of variation of maize and rice yields.. In 31 percent of the maize growing areas of India, maize yields have stagnated; similarly, yields have stagnated in 36 percent of the rice-growing areas and 70 percent of the wheat-growing areas of the country. (Ray et al. 2012). This combination of slowing or stagnant growth and instability in yield could have a significant impact on the vulnerability and viability of small and marginal farmers in India. India is a vast country whose 29 states experience a wide variety of climatic and soil typology. The instability in food grain production is heterogeneous across the states, with greater instability in eastern India's agricultural sector (Chand and Raju 2008).

In a context like this—where increased variability in crop incomes is interacting with variability in climate, with different levels of uptake of modern technology, and with variability in the adoption of adaptation measures by smallholders—formal insurance markets could play an important role in fostering agricultural development, increased productivity, and improved food security in India (Hazell and Hess 2010). The Government of India (GoI) has long recognized the need for crop insurance (CI). It launched crop insurance schemes as early as in 1972, if only on a limited scale; however, crop insurance is only now gaining momentum due to the increased frequency in recent years of extreme climate events, growing agrarian distress, and market reforms. Realizing the inefficiency of existing crop insurance schemes, in 2016, the GoI announced a new insurance scheme called Pradhan Mantri Fasal Bima Yojana (PMFBY). Despite several policy-level experiments in India's crop insurance system, there is very little literature evaluating insurance products in India (Tobacman et al. 2017); most of the studies of crop insurance in India confine themselves to an analysis of its progress, trends, and impediments in implementation (Prabhu and Ramchandran 1986; Sinha 2004; Vyas and Singh 2006; Raju and Chand 2007; Nair 2010; Mukherjee and Pal 2017; Gulati, Terway, Hussain 2018). Furthermore, most of these studies are based on secondary data and cannot capture the nuances at the grassroots level.

This study investigates the relationship between crop insurance and the crop productivity of smallholder farming households in eastern India. First, the study explores the determinants of crop insurance uptake among smallholders producers in the region, including the states of Bihar, West Bengal, Odisha, eastern Uttar Pradesh[4], Jharkhand, and Chhattisgarh. These states were selected because they are located in a similar agro-ecological zone with a similar soil typology; this region was also chosen because it is more risk prone than other parts of India, being relatively underdeveloped with low per capita income, low agricultural productivity and high levels of food

[4] Only eastern part of Uttar Pradesh comes under eastern region of India.

and nutrition insecurity. Second, the study identifies the impact of crop insurance on rice yield. To address these two objectives, the study uses data from an extensive scale survey of smallholder rice farmers in the six states.

The current study contributes to the existing literature in several ways. First, in examining the impact of crop insurance on rice yield, the study has potential relevance to policymakers who are attempting to address risk and uncertainty in rice growing, which in turn affects India's food security. Second, our analysis is very pertinent to policymakers' desire—because of budgetary pressures and pressure to reduce the role of government in the agricultural sector—to find ways to privatize risk management strategies in India. The third and final contribution of this study is the basing of its analysis on a uniquely large representative sample comprised of differently sized farms located across the states of eastern India.

The rest of this paper is organized as follows. The next section gives a brief historical background of crop insurance in India. Section 3 discusses the data.. The conceptual and econometric framework used in the study are discussed in section 4. Section 5 deloberates on results of the study. Finally, conclusions and and policy implications are discussed in Section 6.

## 2. Crop Insurance in India

The proposal for crop insurance in India dates back to as early as 1920. After independence, both central and state governments made several attempts to introduce crop insurance schemes for Indian farmers; the first of these was launched in 1972 and various schemes followed. For a detailed account of the evolution of crop insurance schemes in India, see Raju and Chand 2007, 2008; Gulati, Terway, Hussain 2018. A brief sketch of the evolution of crop insurance in India is given in Table 1. The first countrywide crop insurance scheme, known as the Comprehensive Crop Insurance Scheme (CCIS), was introduced in Kharif 1985; it was based on an area approach, and area units were identified for the purpose of assessing indemnity. The CCIS was replaced by the National Agriculture Insurance Scheme (NAIS) in Rabi 1999/2000, and during Rabi 2010/2011, the Modified National Agricultural Insurance Scheme (MNAIS) was introduced. Besides these schemes, several other pilot projects were implemented over the years, such as the Seed Crop Insurance Scheme (1999/2000), the Farm Income Insurance Scheme (Rabi 2003/2004), and the Weather Based Crop Insurance Scheme (Kharif 2007). Despite all these efforts and the many policy-level experiments, the coverage of farmers under CI in India has historically been low (Dandekar 1976, 1985; Mishra 1995; Sinha 2004; Clarke et al. 2012; Mukherjee and Pal 2017). For a long time, the publicly funded insurance company, the Agricultural Insurance Corporation of India Limited (AIC), was the sole provider of crop insurance in India. In 2016, to overcome the limitations of existing crop insurance systems, the GoI announced the Pradhan Mantri Fasal Bima Yojana (the Prime Minister's Crop Insurance Scheme, or PMFBY), whose objective was to provide adequate insurance coverage and financial support to farmers in the event of crop failure.

**Table 1. Chronology of crop insurance schemes in India**

| Start and end year | Name of crop insurance scheme | Primary feature of the scheme |
|---|---|---|
| 1972–1978 | First individual approach crop insurance scheme | First scheme in India after independence; voluntary and limited in scale |
| 1979–1984 | Pilot Crop Insurance Scheme | First area index-based scheme; confined to loanee farmers; voluntary; 50 percent subsidy on premium for marginal and small farmers |
| 1985–1999 | Comprehensive Crop Insurance Scheme (CCIS) | Crop insurance made mandatory for loanee farmers; available to all; 50 percent subsidy on premium for marginal and small farmers |
| 1997–1998 | Experimental Crop Insurance Scheme (ECIS) | Fully subsidized scheme |
| 1999–2016 | National Agricultural Insurance Scheme (NAIS) | Sharecroppers were included in insurance cover |
| 2003–2004 | Farm Income Insurance Scheme (FIIS) | First scheme to cover farm income rather than cost of cultivation |
| 2007 to present | Weather Based Crop Insurance Scheme (WBCIS) | First scheme to ascertain crop loss based on deviation in rainfall |
| 2010–2016 | Modified National Agricultural Insurance Scheme (MNAIS) | Private sector participation encouraged; immediate partial payment to affected farmers introduced |
| 2016 to present | Pradhan Mantri Fasal Bima Yojana (PMFBY) | Premium rates lowered; use of technology emphasized; heavily subsidized; mandatory to loanee farmers until 2019; voluntary to all from 2020 |

**Source:** Adapted from Mukherjee and Pal (2017).

The PMFBY has at least eight unique features that have gained popularity among food crop and oilseed farmers. (1) The sum insured is determined by the district-level technical committee (DLTC), which takes into account the cost of cultivation based on land quality and irrigation expenses as well as the cost of fertilizer, seeds, and labor. (2) For the Kharif season, the premium rate is fixed at 2 percent of the sum insured or the actuarial rate, whichever is less; for the Rabi season, it is fixed at 1.5 percent of the sum insured or the actuarial rate, whichever is less. The difference between the premium rate and the rate of insurance payable by farmers is shared equally by the central and state governments as a premium subsidy. (3) The estimation of crop yield is based on crop cutting experiments[5] at the village level for four major crops and eight other crops. (4) The PMFBY reserves a bigger role for private insurance companies. (5) Payment must be processed within 30 days of the loss occurrence. (6) Premium subsidies are released to private companies in a timely manner. (7) Modern technology is used, including mobile-based technology, with Global Positioning System (GPS) stamping to assess crop loss. And finally, (8) to publicize the program and raise awareness, the PMFBY conducts significant outreach to farmers through smartphones, electronic and print media, and documentaries. By launching these programs, the GoI has shown its willingness to provide crop insurance to a larger number of farmers and to allow increased participation by private insurance companies. In the last two seasons—Kharif 2016 (India, Ministry of Agriculture and Farmers Welfare 2016a) and Rabi 2016/2017 (India, Ministry of Agriculture and Farmers Welfare 2016b)—approximately 55 million hectares have been insured under the PMFBY. Initially, this scheme was mandatory for loanee farmers. However, the Government of India has recently revamped the PMFBY and the scheme is now optional for all farmers from Kharif 2020 (Press Information Bureau 2020).

[5] Crop Cutting Experiments or CCE, refer to an assessment method employed by governments and agricultural bodies to accurately estimate the yield of a crop or region during a given cultivation cycle. The traditional method of CCE is based on the yield component method where sample locations are selected based on a random sampling of the total area under study. Once the plots are selected, the produce from a section of these plots is collected and analysed for a number of parameters such as biomass weight, grain weight, moisture, and other indicative factors. The data gathered from this study is extrapolated to the entire region and provides a fairly accurate assessment of the average yield of the state or region under study.

## 3. Survey Data

This study uses data from a primary survey conducted in six states in eastern India, namely Bihar, Chhattisgarh, Jharkhand, Odisha, eastern Uttar Pradesh,[6] and West Bengal in 2016-17. This eastern region is considered to be relatively poor and to have higher levels of undernourishment than other parts of the country, accounting for more than 50 percent of India's poor and food insecure population. The region is predominantly agrarian, and farms are mostly small and marginal with limited resources. Smallholders in this region face several challenges, including recurrent floods and droughts, cyclones, and numerous pests and diseases; farmers also face severe constraints like rising input prices, declining farm profits, and an increasing strain on natural resources. Rice is the major crop, accounting for about 60 percent of the total cropped area. From each of the six states, 13 predominantly rice-growing districts were selected (Figure 1); within each district, three blocks were randomly sampled, and within each block, we then randomly sampled two villages. A house listing was conducted in each village to obtain a large sample of farm households, from which we randomly selected 20 households to survey. In this way, we collected data from 78 districts spread over 468 villages, and the final sample, after data cleaning, consisted of 8055 farm households. We had to dropped some observations due to extreme oultiers and non-sampling error. The survey queried farmers on various operator and household characteristics, sources of information, variety adoption, credit, and insurance.

[6] We considered only eastern Uttar Pradesh as other parts of the state are not in the eastern region of the country.

**Figure 1. Surveyed states and districts of eastern India**


**Source:** IFPRI survey: mapping the adoption of improved varieties and management practices in eastern India.

Table 2 presents the definition and summary statistics of the variables used in this study. It indicates that there are significant differences between insured and uninsured rice farmers in eastern India; for instance, while the average rice yield is about 23.47 quintals/hectare (q/ha), the yield among insured rice farmers is 25.03 q/ha and among uninsured rice farmers is 22.14 q/ha, a difference that is statistically significant at the 1 percent confidence level. Table 2 also shows significant statistical differences between insured and uninsured farmers in various demographic, agricultural, and socioeconomic characteristics. Within the sample group, the average number of years of education attained by rice producers was about 6.43 years, but the education level was lower among insured than uninsured farmers. Caste is a uniquely Indian social institution that plays a vital role in economic life, schooling, income, food, and access to inputs and services.[7] Table 2 reveals that almost half the farmers belonged to Other Backward Classes (OBCs), 20 percent of the farmers belonged to the General caste category, 13 percent belonged to Scheduled Castes (SCs), and 19 percent belonged to Scheduled Tribes (STs). Historically, SCs and STs lag behind other caste categories in many socioeconomic indicators; in particular, they have had less access to land and assets than OBCs and members of General castes. Table 2 shows that among insured farmers, 12 percent belonged to General castes, 50 percent were OBCs, 27 percent were SCs, and the remaining 10 percent were STs. Because of different caste compositions in each of the states, percentages varied from state to state. Chhattisgarh and Jharkhand, for instance, had a larger percentage of farmers belonging to STs, who therefore constituted a larger proportion of the insured farmers. The average household size of smallholder rice producers was about seven, but insured families had fewer uninsured families (statistically significant at the 1 percent level). Insured farmers had slightly more farming experience than uninsured farmers (25 years as compared to 24 years). A higher proportion of insured rice farmers had borrowed money (27.0 percent) than had uninsured rice farmers (14.2 percent); this finding is not surprising as access to crop insurance is closely linked to access to credit, and crop insurance is mainly sold through banks and private enterprises.

[7] The caste system is comprised of four hierarchical categories, the Brahmins, Kshatriyas, Vaishyas, and Shudras. These castes are classified as Scheduled Castes (SCs), the socially and economically marginalized, indigenous ethnic groups that are classified as Scheduled Tribes (STs), and, more recently, another group of castes, which are referred to as Other Backward Castes (OBC's).

In terms of farm size, insured farmers owned about 1.33 ha of land, while uninsured farmers owned about 1.04 ha. Among farmers in the sample, 57 percent did not have access to any source of irrigation, 32 percent had access to groundwater irrigation, including pumps and tube wells, and 11 percent had access to surface water irrigation, including canals, rivers, and ponds. As shown in Table 2, a larger proportion of insured farmers had no source of irrigation, and a larger share of uninsured rice farmers had access to groundwater irrigation. These findings may indicate that rice farmers with a more dependable water source, in groundwater irrigation, may feel less need for crop insurance than do farmers with no reliable water supply. These findings may indicate that rice farmers with a more dependable water source, in groundwater irrigation, may feel less need for crop insurance than do farmers with no reliable water supply. In terms of land typologies based on elevation,[8] around three-fifths of the rice farmers had plots at what is classified as a medium elevation, around 29 percent had plots on lowlands, and about 10 percent had plots in upland areas. Rice is typically cultivated at a medium elevation; a study in eastern India and Bangladesh (Hossain et al. 2013) found a similar distribution of rice cultivation across medium, low, and upland elevations.

Apart from agricultural characteristics, Table 2 reveals significant differences in other socioeconomic characteristics of insured and uninsured rice farmers in eastern India. Table 2 also shows the characteristics of soil type and color. More than one-third of the rice farms had sandy loam soil, followed by sandy (23.6 percent), clay (19.3 percent) and loam (18.9 percent) soils; more than half of the rice farmers had brown soil, close to one-third had black soil, and the rest

[8] Technically, the classification of lowlands, medium elevations, and uplands occurs based on the distance of the land above sea level. A land elevation of less than 200 meters above sea level (MASL) is considered to be lowlands, land above 500 MASL is uplands, and 200 to 500 MASL is medium elevation (Meybeck et al 2001). Our variable, however, is based on responses by farmers as to where their land is located; land located at elevations that are higher than typical village plots is generally referred to by farmers as uplands, and plots at elevations lower than typical village plots is classified as lowlands; plots at average village-level elevations are considered to be at a medium elevation.

(16.2 percent) had yellow soil. Among insured rice farmers, 15 percent had soil health cards, as compared to only about 4 percent among uninsured rice farmers.

Table 2 further shows that insured rice farmers cultivate an average of two crops, while uninsured farmers cultivate, on average, one crop. We also found more insured than uninsured rice farmers to be engaged in livestock production and found them, as a group, to own more cattle. This suggests that risk aversion is the characteristic that motivates a farmer to acquire crop insurance, diversify into livestock, and grow more than one crop (Ehrlich and Becker 1972). We also found that insured farmers changed their wheat variety three years sooner than did uninsured rice farmers.

**Table 2. Variable description and summary statistics, eastern India, 2016**

| | Crop insurance (N = 3707) | | No crop insurance (N = 4348) | | Diff | All (N = 8055) | |
|---|---|---|---|---|---|---|---|
| | M | SD | M | SD | | M | SD |
| **Outcome variable** | | | | | | | |
| Rice yield (quintals/hectare) | 25.03 | 10.70 | 22.14 | 10.26 | 2.88*** | 23.47 | 10.56 |
| **Explanatory variables** | | | | | | | |
| Education (years) | 6.30 | 4.59 | 6.54 | 4.58 | -0.24* | 6.43 | 4.59 |
| **Social caste (%)** | | | | | | | |
| Scheduled Castes[1] | 10.41 | 30.55 | 15.27 | 35.98 | -4.86*** | 13.04 | 33.67 |
| Scheduled Tribes[1] | 27.49 | 44.65 | 13.09 | 33.73 | 14.40*** | 19.71 | 39.79 |
| Other Backward Classes[2] | 50.34 | 50.01 | 44.78 | 49.73 | 5.56*** | 47.34 | 49.93 |
| General caste | 11.57 | 31.99 | 26.43 | 44.10 | -14.85*** | 19.59 | 39.69 |
| Household members (number) | 6.60 | 3.09 | 6.93 | 3.83 | -0.33*** | 6.78 | 3.51 |
| Farming experience (years) | 25.12 | 11.39 | 24.14 | 11.94 | 0.98*** | 24.59 | 11.70 |
| Borrowed money (%) | 27.02 | 44.41 | 14.21 | 34.92 | 12.81*** | 20.11 | 40.08 |
| Land size (hectares) | 1.33 | 1.80 | 1.04 | 1.65 | -0.29*** | 1.17 | 1.73 |
| **Irrigation source (%)** | | | | | | | |
| Rainfed | 65.98 | 47.38 | 49.03 | 50.00 | 16.95*** | 56.83 | 49.53 |
| Groundwater | 20.26 | 40.20 | 42.57 | 49.45 | -22.31*** | 32.30 | 46.77 |
| Surface water | 13.76 | 34.45 | 8.39 | 27.73 | 5.36*** | 10.86 | 31.12 |
| **Land typology (%)** | | | | | | | |
| Lowlands | 27.76 | 44.79 | 30.63 | 46.10 | -2.88** | 29.31 | 45.52 |
| Medium elevation | 62.72 | 48.36 | 59.75 | 49.05 | 2.97** | 61.12 | 48.75 |
| Uplands | 9.52 | 29.36 | 9.61 | 29.48 | -0.09 | 9.57 | 29.42 |
| **Soil type (%)** | | | | | | | |
| Sandy | 29.13 | 45.44 | 18.91 | 39.16 | 10.23*** | 23.61 | 42.47 |
| Sandy loam | 33.50 | 47.21 | 42.09 | 49.38 | -8.58*** | 38.14 | 48.58 |
| Loam | 14.03 | 34.73 | 23.05 | 42.12 | -9.02*** | 18.90 | 39.15 |
| Clay | 23.33 | 42.30 | 15.96 | 36.63 | 7.37*** | 19.35 | 39.51 |
| **Soil color (%)** | | | | | | | |
| Black | 33.64 | 47.25 | 24.22 | 42.85 | 9.42*** | 28.55 | 45.17 |
| Brown | 54.22 | 49.83 | 56.12 | 49.63 | -1.90 | 55.25 | 49.73 |
| Yellow or red | 12.14 | 32.66 | 19.66 | 39.75 | -7.53*** | 16.20 | 36.85 |
| Soil health card holder (%) | 14.89 | 35.60 | 4.60 | 20.95 | 10.29*** | 9.34 | 29.10 |
| Number of crops cultivated | 1.56 | 0.71 | 1.23 | 0.53 | 0.33*** | 1.38 | 0.64 |
| Number of cattle | 3.20 | 2.63 | 2.23 | 2.03 | 0.97*** | 2.67 | 2.37 |
| Varietal age (years) | 18.25 | 14.63 | 20.99 | 15.83 | -2.75*** | 19.73 | 15.35 |

**Source:** IFPRI survey: mapping the adoption of improved varieties and management practices in eastern India.
**Note:** [1] *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels; M, N and SD indicate mean, number and standard deviation, respectively.

## 4. Conceptual and Empirical Framework

In the context of crop insurance and farm production, conceptual studies such as those by Ramaswami (1993), Chambers and Quiggin (2002), and Carter, Cheng, Sarris (2016) provide a framework for the impact of crop insurance on the reallocation of farm resources. Ramaswami (1993), in a model with single and multiple input production functions under an expected utility framework, examines the effect of crop insurance on supply response; the effect of insurance is deconstructed into risk reduction and moral hazard, and results suggest that the direction of the effect of insurance on supply response is ambiguous. Chambers and Quiggin (2002) use the Arrow-Debreu state-contingent approach; they investigate the link between a crop producer's insurance choice and their production decisions when area-yield insurance is available; they provide a sufficient condition for the provision of area-yield insurance to induce a change toward riskier production patterns. Ahsan, Ali, Kurian (1982) showed that with a single input and single uncertain output, crop insurance promotes agricultural output. Other studies in the literature show that CI changes the plating structure (Wu 1999; Young, Vandeveer, Schnepf 2001). In the early 2000s, Hau (2006) examined the impact of the output decision of a risk-averse producer facing profit-risk (price and output uncertainty). Consistent with Ahsan, Ali, Kurian (1982), Hau's analysis reveals that under certain conditions, CI can increase agricultural output.

We have employed the following econometric tools to construct our empirical model of the impact of CI on rice yield in eastern India. Rice is the most crucial individual source of dietary energy in the region, providing 58.1 percent of dietary calories and 46.4 percent of total dietary protein. Across the states of this region, between 8.3 and 24 percent of a family's food budget is spent on rice, with the poor spending a relatively larger share of their income. To understand the impact of CI on rice yield, we use an ex-post evaluation approach through counterfactual evidence-based statistical analysis. We consider the adoption of CI as a treatment provided to farmers and use different econometric tools to deal with selection bias and treatment endogeneity; application of different models also ensures the consistency and robustness of our findings. A brief description of these econometric approaches is given below.

### 4.1. Propensity Score Matching

In propensity score matching (PSM), we build counterfactuals to minimize the problems occurring from selection bias from the sample. The objective behind using this technique is to find a group of uninsured farmers (control group) that is similar to the insured farmers (treatment group) in all relevant observable features; in this case, PSM helps to generate the average treatment effect for the treatment group (ATT). There are several methods for matching the propensity scores of the treatment and control groups, namely the nearest neighbor method (NNM), kernel method, radius matching, and bootstrapping. In general, all these methods should yield the same results; however, in practical scenarios, with each method, there are trade-offs in terms of bias and efficiency (Caliendo and Kopeinig 2008). In our study, using the PSM method, we use the kernel, NNM, and radius techniques. We have highlighted the results of the NNM technique, in which the basic idea is to find the "neighboring" value (propensity score) of control farmers, that is, the value which is closest to the values of treated farmers. The main objective of the propensity score estimation is to balance the observed distribution of covariates across the treatment groups and control groups. The balancing test is usually required after the matching exercise is completed; it also helps to ascertain whether the differences in covariates in the two groups of the matched sample have been eliminated or not. If the differences between the two groups are abolished, then the matched comparison group can be considered a plausible counterfactual (Ali and Abdulai 2010). Different interpretations of the balancing test exist, but the most frequently used standardized mean difference (bias) between treatment and control groups should be minimized significantly. In principle, after matching, there should be no systematic differences in the distribution of covariates between the groups (Rosenbaum and Rubin 1985).

Let $D_i$ be an indicator of whether a farmer is insured or uninsured. The potential productivity outcome of uptake of insurance, represented by $i$, for each farmer is defined as ($D_i$). The ATT is calculated as:

$$\Delta_{ATT} = E(\Delta|D_i = 1) = E[(\tau\ (1)|D_i = 1] - E[(\tau\ (0)|D_i = 1], \quad (1)$$

where $\Delta_{ATT}$ is the average treatment effect on the treated, $E[(\tau\ (1)|D_i = 1]$ is the expected outcome variable of an insured farmer, and $E[(\tau\ (0)|D_i = 1]$ is the expected outcome variable of a treatment farmer if they have not taken insurance. The PSM technique involves the imposition of conditional independence and common-support assumptions for identification. If the above two assumptions are fulfilled, then the PSM estimator for ATT is given as follows:

$$\Delta\frac{PSM}{ATT} = E_{p(X)|D_i=1}\{E[(\tau\ (1)|D_i = 1, p(X)] - E[(\tau\ (0)|D_i = 1, p(X)]\} \quad (2)$$

We use the nearest neighbor matching algorithm for our discussion, which attempts to estimate the effect of insurance by accounting for the covariates that predict receiving the treatment. PSM estimators do not account for selection on unobservable factors; hence, we accept that such selection bias has little impact on our results. As mentioned earlier, in our sample, we had about 8,788 observations, but after matching approach, we used 8,055 matched samples obtained from the PSM approach.

### 4.2. Coarsened Exact Matching

Coarsened exact matching (CEM) is an alternative technique to PSM, belonging to the monotonic imbalance bounding (MIB) group developed by Iacus, King, and Porro (2012). CEM works in sample distributions and requires no assumption about the data generation process except for the usual ignorability assumptions. This method ensures that the imbalance between the matched and unmatched groups will not be greater than the ex-ante choice mentioned by the user. Iacus, King, Porro (2012) and King et al. (2011) have shown that CEM dominates commonly used matching methods to reduce imbalance, model dependence, estimation error bias, variance, and mean square error. CEM is designed to coarsen each variable by recoding so that considerable identical values are grouped and assigned the same values; the exact matching principle follows this to determine the matches and to trim unmatched units. Finally, the coarsened data is withdrawn, and the original values of the matched data are retained.

After coarsening, the CEM creates a set of strata, say $s \in S$, each with a few coarsened values of $X$. Consider a sample of size $n$ ($n \leq N$) which contains units drawn from population $N$. Let $T_i$ denote an indicator variable for unit $i$ which takes the value 1 if the $i^{th}$ unit belongs to the treated group and takes the value 0 if the $i^{th}$ unit belongs to the control group. The observed outcome variable $Y_i = T_i Y_i(1) + (1-T_i) Y_i(0)$ where $Y_i(0)$ is the outcome for the non-beneficiary group and $Y_i(1)$ is the outcome for the beneficiary group. To estimate the impact of technology intervention on a selected group of households, the standard ignorability assumption is made, which states that conditional on $X$, the treatment variable is independent of the potential outcomes and every treated unit receives the same treatment. A fixed causal effect is a function of the potential outcome, defined as $Y_i(1) - Y_i(0)$. The estimates for the causal impact on outcome variables can be defined as:

$$SATT = \frac{1}{n_T} \sum_{i \varepsilon \tau} TE_i, \tag{3}$$

where $TE_i = Y_i(1) - Y_i(0) \mid X_i$, and $n_T$ = total number of treated units in the original sample. This estimate is valid only when all treated units are matched; however, in our case, when all the units do not match, the SATT changes to LSATT or local sample average treatment for all treated, and the estimate is given by:

$$LSATT = \frac{1}{m_T} \sum_{i \varepsilon \quad m} TE_i, \tag{4}$$

where $m_T$ is the number of matched treated units and $T^m$ is the subset of matched treated units.

### 4.3. Endogenous Switching Regression

Matching techniques—regardless of adjustments for misspecification bias—can overcome only the selection bias caused by observables. When the endogeneity bias is due to unobservable heterogeneity, the matching techniques will be biased. Therefore, to account for both observed and unobserved sources of bias, we employ an endogenous switching regression (ESR) framework to estimate the parameters. The ESR approach addresses this endogeneity problem by estimating the selection and outcome equations simultaneously using the full information maximum likelihood (Lokshin and Sajaia 2004; Ma and Abdulai 2016; Wossen et al. 2017; Mishra et al. 2018; Kumar et al. 2018). We specify the selection equation for the uptake of crop insurance as:

$$T_i^* = X_i\alpha + \delta_i \text{ with } T_i = \begin{cases} 1 \text{ if } T_i^* > 0 \\ 0 \text{ otherwise} \end{cases} . \quad (5)$$

That is, a farmer will take crop insurance ($T_i = 1$), if $Y^* > 0$, where $Y^*$ represents the expected benefits of insured farmers compared to uninsured farmers.

Here, $X$ is a vector of variables that determine an farmer's output. The relationship between a vector of explanatory variables $X$ and the outcome $Y$ can be represented by $Y = \mathrm{f}(X)$. Specifically, the outcome function conditional on treatment can be represented as follows:

$$\text{Regime 1: } Y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \text{ if } T_i = 1$$

$$\text{Regime 2: } Y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i} \text{ if } T_i = 0 , \quad (6)$$

where $Y_i$ is the outcome of interest—that is, rice yield (q/ha) in regimes 1 and 2 of equation 6—and $X_i$ represents a vector of the explanatory variables; $\varepsilon_i$ is the error term of the outcome variable. Finally, the error terms are assumed to have a trivariate normal distribution, with 0 mean and covariance matrix. If the estimated covariances between $\delta$ and $\varepsilon$'s ($\rho_1$ and $\rho_2$, respectively) are statistically significant, then the insured farmers' characteristics and the outcome variable are correlated. The $\rho_1$ and $\rho_2$ are the transformation of the correlation between the errors from equation 6. Using this method, we found evidence of endogenous switching and rejected the null hypothesis that sample selectivity bias was absent. This model is defined as a "switching regression model with endogenous switching" (Maddala and Nelson 1975), which can be used to estimate the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU).

Identification of the ESR model requires at least one additional variable as an instrument. The selection of instrumental variables should directly affect the selection variable but not the outcome variable. In this study, as an instrumental variable we have taken bank density[9] at district level. We established the admissibility of the instruments by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the households of farmers who had taken insurance but will not affect the outcome variable of the households of farmers who had no crop insurance.

In addition to using the ESR model, we calculated the average treatment effect (ATE) of CI on rice yield using the endogenous switching regression model as mentioned below:

a. $E(Y_{1i}|T_i = 1) = [\sum_{\mathrm{Ti=}} (X_{1i}\beta_1 + \sigma_{1n}\gamma_{1i})]/N_1$ (7)

b. $E(Y_{2i}|T_i = 0) = [\sum_{\mathrm{Ti=0}}(X_{2i}\beta_2 + \sigma_{2n}\gamma_{2i})]/N_0$ (8)

c. $E(Y_{2i}|T_i = 1) = [\sum_{\mathrm{Ti=1}}(X_{1i}\beta_2 + \sigma_{2n}\gamma_{1i})]/N_1$ (9)

d. $E(Y_{1i}|T_i = 0) = [\sum_{\mathrm{Ti=0}}(X_{2i}\beta_1 + \sigma_{1n}\gamma_{2i})]/N_0$ . (10)

$N_1$ and $N_0$ are the number of observations with $T_i = 1$ and $T_i = 0$, respectively.

[9] We have defined bank density as a proportion of number of functional banks to area (square kilometre) of district. We have obtained functional bank information from RBI Branch Banking Statistics as of 2018 and area of district information from Census 2011.

Cases (a) and (b) in Table 3 represent the actual expectations observed in the sample, and cases (c) and (d) represent the counterfactual expected outcomes; however, following Heckman, Tobias, Vytlacil (2001), we calculated the effect of the treatment (insured farmers) on the treated (TT) as the difference between (a) and (c), which represents the impact of crop insurance on the outcome variable of the farm households that have crop insurance; similarly, we calculated the difference between (d) and (b) as the effect of the treatment on the untreated (TU) for the farm households that did not have crop insurance.

We also defined the "the effect of base heterogeneity" for the group of farm households that decided to opt for crop insurance as the difference between (a) and (d); for the group of farm households that decided not to opt for crop insurance, the effect of base heterogeneity was defined as the difference between (c) and (b) (Carter and Milon 2005). Finally, we examined the transitional heterogeneity (TH), that is to say, whether the effect of crop insurance on the outcome variable is larger or smaller for farm households that had taken crop insurance than for those that had not taken crop insurance in the counterfactual case (that is, the difference between TT and TU).

**Table 3. Treatment and heterogeneity effect: decision stage**

| **Transitional heterogeneity** | **Decision stage** | | **Treatment effects** |
|---|---|---|---|
| | **Insured** | **Uninsured** | |
| Insured | (a) $E(Y_{1i} \mid B_i = 1)$ | (c) $E(Y_{2i} \mid B_i = 1)$ | TT |
| Uninsured | (d) $E(Y_{1i} \mid B_i = 0)$ | (b) $E(Y_{2i} \mid B_i = 0)$ | TU |
| Heterogeneity effects | $BH^1$ | $BH^2$ | TH |

**Source:** Carter and Milon 2005.

**Note:** (a) and (b) represent observed expected outcome indicators; (c) and (d) represent counterfactual expected outcome indicators; $B_i$ = 1 if farmers have opted for crop insurance; $B_i$ = 0 if farmers have not opted for crop insurance; $Y_{1i}$ = outcome indicators if farmers have opted for crop insurance; $Y_{2i}$ = outcome indicators if farmers have not opted for crop insurance; TT = the effect of the treatment (that is, farmers with crop insurance) on the treated (farmers without crop insurance); TU = the effect of the treatment (that is, insured) on the untreated (uninsured); $BH_i$ = the effect of base heterogeneity for farmers with crop insurance ($i$ = 1), and farmers without crop insurance ($i$ = 2); TH = (TT − TU) (that is, transitional heterogeneity).

# 5. Results and Discussion

In the next section, we first discuss the determinants of adoption of crop insurance based on the selection equations in Tables 7; we then discuss the impact of crop insurance on rice yield, based on the estimates obtained from alternative econometric models.

## 5.1. Determinants of Crop Insurance

In this section we will focus on estimates obtained from the ESR model for drivers of crop insurance. Table 7 Column 3 suggests the drivers of farming households' decisions to opt for crop insurance; many factors may affect this decision, including the farmer's caste, farming experience, farm size, possession of soil health card, access to institutional credit, and possession of livestock. The coefficient of land size is positive and significant at the 5 percent level of significance; this suggests that large farmers are likely to opt for crop insurance. Belonging to general castes shows a positive correlation with crop insurance. Years of farming experience of the head of household (HH) is significantly and positively correlated with crop insurance; a possible explanation for this is that experience enhances the farmer's awareness of the need to ensure both technical and allocative efficiency of resources. Medium elevation rice farmers have a positive and significant coefficient for the adoption of CI as compared to lowland rice farmers; this suggests that lowland farmers enjoy better availability of water and better yields and are thus are less risk-prone. Rice farmers farming on sandy loam soil have a negative and significant coefficient with CI as compared to rice farmers with sandy soil. Farmers with soil health cards—which are basically for soil quality monitoring and routine field observations by farmers—are more likely to adopt crop insurance; one reason for this could be that soil health cards enable farmers to understand soil conditions better and thus they are motivated to opt for crop insurance. Rice farmers who have obtained loans from banks are more likely to adopt crop insurance, a finding which is not surprising as access to CI is closely linked to access to credit through institutional financial sources. Finally, farmers with more livestock have a higher probability of opting for crop insurance.

## 5.2. Impact of Crop Insurance on Rice Yield

This section highlights the impact of crop insurance on rice yield in eastern India based on PSM, CEM and ESR models.

### 5.2.1. Estimates from a propensity score matching model

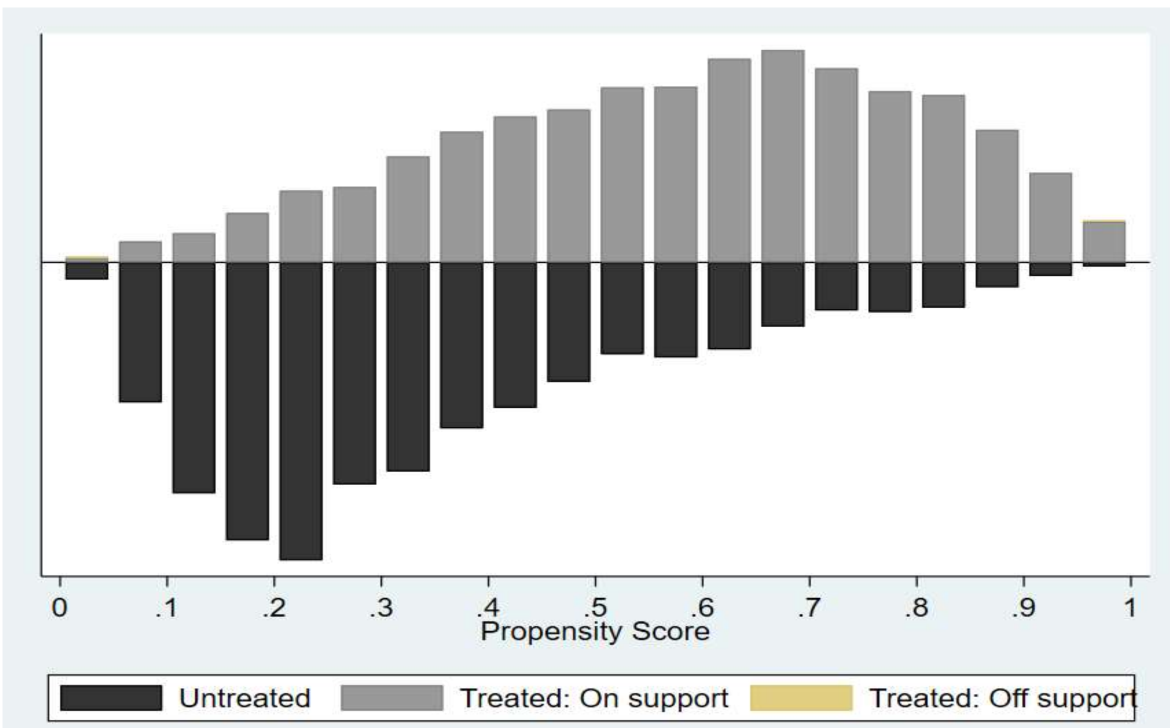
Using a propensity score matching (PSM) method, we performed matching of covariates using logistic regression. In this section, we describe the matching process and common-support technique, followed by a discussion of ATT estimates in a later section. The method of kernel density, nearest neighbor, and radius methods were applied while matching the covariates. Figure 2 helps us to confirm that the distribution of propensity scores through the common-support condition is satisfied, as we can observe that there is a substantial overlap in the distribution of the propensity scores of both treated and untreated groups. The upper half refers to the propensity score distribution of treated individuals and the bottom half refers to the control (untreated) group. Table 4 gives us the estimates of rice yield (ATT) by all three matching techniques. The results show that insured farmers had higher rice yields than uninsured farmers. The rice yield for the treated group is calculated as 25.03 q/ha and the yield for the untreated group is only 21.82 q/ha (NNM = 3); the impact of crop insurance is thus clearly visible as the rice yield of the insured and uninsured groups of rice farmers differs by 3.21 q/ha. In the case of other matching techniques, we found a positive treatment effect that ranged from 3.01 q/ha to 3.08 q/ha. The robustness of our results across all matching estimates is thus evident.

**Table 4. Impact of crop insurance on rice yield (q/ha) using a propensity score matching (PSM) technique**

| PSM techniques | | Treatment | Control | Difference | SE | t-stat |
|---|---|---|---|---|---|---|
| Kernel | 0.01 | 25.03 | 22.02 | 3.02*** | 0.31 | 9.78 |
| | 0.05 | 25.03 | 21.96 | 3.08*** | 0.30 | 10.15 |
| NNM | N = 1 | 25.03 | 21.52 | 3.52*** | 0.37 | 9.42 |
| | N = 3 | 25.03 | 21.82 | 3.21*** | 0.33 | 9.84 |
| | N = 5 | 25.03 | 21.88 | 3.16*** | 0.32 | 9.91 |
| Radius | 0.01 | 25.03 | 22.02 | 3.01*** | 0.31 | 9.81 |
| | 0.05 | 25.03 | 21.95 | 3.08*** | 0.30 | 10.21 |

**Source:** Author's calculation.
**Note:** SE = Standard error; NNM = nearest neighbor matching; *** indicate statistical significance at p < 0.01 level.

**Figure 2. Common-support region**




**Source:** Author's calculation.

Table 5 presents the covariates balancing tests before and after matching, using the nearest neighbor method. The output generated from this matching procedure is robust and significant at a 95 percent level of significance, satisfying the aptness of the matching algorithm applied. The values indicate that there is substantial reduction in bias after the matching technique is executed. The *'p*-value' of the likelihood ratio indicates that the joint significance of covariates was rejected after matching. The low mean standardized bias and joint insignificance of the covariates are indicative of successful balancing of the distribution of covariates between treated and untreated households.

**Table 5. Propensity score matching quality test**

| Quality test | Unmatched | Matched |
|---|---|---|
| Pseudo R2 | 0.191 | 0.007 |
| LR$\chi$2 (*p*-value) | 2123.15<br>(0.000) | 69.14<br>(0.000) |
| Mean standardized bias | 20.08 | 3.80 |

**Source:** Author's calculation.

### 5.2.2. Estimates from the coarsened exact matching method

Matching is a popular method of processing data to improve causal inferences derived from observational data (Ho et al. 2007; Morgan and Winship 2014). PSM is the most popular method of deriving such inferences, but it also leads to an increase in imbalance, inefficiency, model dependence, research discretion, and statistical bias in the model (King and Nielsen 2019); therefore, to reduce the biases and inefficiencies generated from using PSM, we apply the coarsened exact matching (CEM) method to get a more appropriate calculation of the impact of crop insurance on farmers' rice yields. The results obtained from using the CEM model are shown in Table 6. We find that farmers with crop insurance have a 5 percent higher yield than uninsured farmers.

**Table 6. Impact of crop insurance on rice yield (q/ha) using coarsened exact matching method**

| Variables | Coefficient |
|---|---|
| Crop insurance^ | 0.052* |
| | (0.029) |
| Education in years (*log*) | 0.009 |
| | (0.015) |
| **Social Caste: Base—Scheduled Caste^** | |
| Scheduled Tribe^ | -0.127*** |
| | (0.049) |
| Other Backward Classes^ | -0.020 |
| | (0.041) |
| General caste^ | 0.014 |
| | (0.050) |
| Household members (number) (*log*) | -0.027 |
| | (0.033) |
| Farming experience (years) (*log*) | -0.050* |
| | (0.029) |
| Land size (hectares) (*log*) | -0.019 |
| | (0.014) |
| **Irrigation: Base—rainfed^** | |
| Groundwater^ | 0.090*** |
| | (0.031) |
| Surface water^ | -0.062 |
| | (0.084) |
| **Land typology: Base—lowlands^** | |
| Medium elevation^ | 0.002 |
| | (0.039) |
| Uplands^ | 0.125* |
| | (0.064) |
| **Soil type: Base—sandy^** | |
| Sandy loam^ | -0.018 |
| | (0.044) |
| Clay^ | -0.035 |
| | (0.050) |
| Loam^ | 0.006 |
| | (0.053) |
| **Soil color: Base—black^** | |
| Brown^ | -0.100*** |
| | (0.036) |
| Yellow or red^ | -0.098* |
| | (0.054) |
| Soil health card^ | -0.267* |
| | (0.143) |
| Borrowed money^ | 0.109** |
| | (0.048) |

| Variables | Coefficient |
|---|---|
| Number of crops cultivated | 0.004 |
| | (0.029) |
| Number of cattle (*log*) | 0.020 |
| | (0.023) |
| Varietal age (years) (*log*) | 0.015 |
| | (0.010) |
| Constant | 3.195*** |
| | (0.124) |
| State fixed effect | Yes |
| Observations | 2,675 |
| R-squared | 0.131 |

**Source:** Author's calculation.
**Note:** Robust standard errors in parentheses; *, **, and *** indicate statistical significance at the p < 0.1, p < 0.05, and p < 0.01 levels; ^ = binary variable.

### 5.2.3. Estimates from an endogenous switching regression model

Table 7 reports the parameter estimates of the endogenous switching regression model estimated by full information maximum likelihood (FIML) procedures. The results of the outcome equation that assesses the impact of crop insurance on rice yield are shown in Table 7 Columns 1 and 2; Column 3 reports the selection equation that represents the determinants of crop insurance (already discussed above). The estimated coefficient of correlation ( $\rho_j$ ) is statistically significant in either function. This finding suggests that we failed to reject the null hypothesis that sample selectivity bias was absent in both equations; nevertheless, we found a difference between the coefficient of the rice yield function for insured farmers and uninsured farmers, indicating the presence of heterogeneity in the sample. The possible explanation of ( $\rho_j$ ) significance in either function is that those farmers who have crop insurance have better rice yields irrespective of whether they have insurance or are *better off* when they opt for crop insurance.

Table 7 Column 1 reflects the parameters of rice yield for insured farmers. We found that farmers who irrigate using ground and surface water and farmers who borrowed money were positively associated with rice yield for insured farmers; on the other hand, farmers belonging to Scheduled Tribes, farmers with fewer years of farming experience, smaller landholdings, land at medium elevations, farmers with sandy loam, clay, loam and brown soils, and farmers cultivating a smaller number of crops were negatively associated with rice yield for insured farmers.

Soil type and color are associated with rice yield.[10] Our results show that black soil is associated with the highest yields, as per expectations, but we find clay, loam, and sandy loam soils to have lower productivity than sandy soils. The variance can be due to farmers' perceptions and not necessarily because of outcomes of soil tests; however, when we consider uninsured farmers (Table 7 Column 2), other parameters such a farmers education, groundwater irrigation, different soil types (sandy loam and clay), soil color (yellow), and farmers who borrowed money had positive associations with rice yield.

[10] The relation between crop yields and soil color, texture, and other characteristics has been explored in detail in the Indian context (Arakeri et. al 1967). Typically, black soil has higher moisture retention and medium erosivity, as compared to brown soil, while yellow and red soils have low moisture retention and medium erosivity (Desbiez et al. 2004); in general, the darker the soil the higher the productivity. Soil with more clay is expected to provide better yield than sandy soil (Dou et al. 2016).

**Table 7. Impact of crop insurance on rice yield (q/ha) using endogenous switching regression model**

| | Insurance = 1 (farmers who had taken crop insurance) | Insured = 0 (farmers who did not taken crop insurance) | Insured = 1, 0 = otherwise | OLS |
|---|---|---|---|---|
| **Column** | **1** | **2** | **3** | **4** |
| **Dependent variable** | **Yield (ha)** | **Yield (ha)** | **Insured^** | **Yield (ha)** |
| Crop insurance^ | | | | 0.058*** |
| | | | | (0.014) |
| Education (years) (*log*) | 0.003 | 0.018* | 0.019 | 0.011* |
| | (0.009) | (0.009) | (0.019) | (0.006) |
| **Social Caste: Base—Scheduled Castes^** | | | | |
| Scheduled Tribes^ | -0.113*** | -0.079** | -0.083 | -0.107*** |
| | (0.027) | (0.031) | (0.064) | (0.020) |
| Other Backward Classes^ | 0.018 | 0.021 | -0.007 | 0.014 |
| | (0.025) | (0.024) | (0.055) | (0.017) |
| General castes^ | -0.012 | 0.037 | 0.022 | 0.027 |
| | (0.033) | (0.025) | (0.063) | (0.020) |
| Household members (number) (*log*) | -0.002 | -0.009 | -0.097** | -0.013 |
| | (0.020) | (0.019) | (0.041) | (0.014) |
| Farming experience (years) (*log*) | -0.028* | 0.010 | 0.107*** | 0.001 |
| | (0.015) | (0.014) | (0.030) | (0.010) |
| Land size (hectares) (*log*) | -0.021*** | -0.016* | 0.038** | -0.016*** |
| | (0.008) | (0.009) | (0.019) | (0.006) |
| **Irrigation: Base—rainfed^** | | | | |
| Groundwater^ | 0.063*** | 0.085*** | -0.225*** | 0.068*** |
| | (0.020) | (0.023) | (0.050) | (0.015) |
| Surface water^ | 0.088*** | 0.012 | -0.152*** | 0.046** |
| | (0.023) | (0.033) | (0.057) | (0.019) |
| **Land typology: Base—lowlands^** | | | | |
| Medium elevation^ | -0.052*** | -0.017 | 0.177*** | -0.022 |
| | (0.018) | (0.020) | (0.040) | (0.013) |
| Uplands^ | 0.030 | 0.003 | 0.177*** | 0.020 |
| | (0.032) | (0.029) | (0.067) | (0.021) |
| **Soil type: Base—sandy^** | | | | |
| Sandy loam^ | -0.038* | 0.074*** | -0.232*** | 0.006 |
| | (0.019) | (0.026) | (0.050) | (0.015) |
| Clay^ | -0.078*** | 0.110*** | -0.080 | -0.047** |
| | (0.025) | (0.033) | (0.063) | (0.019) |
| Loam | -0.102*** | 0.042 | -0.372*** | 0.017 |

| | Insurance = 1 (farmers who had taken crop insurance) | Insured = 0 (farmers who did not taken crop insurance) | Insured = 1, 0 = otherwise | OLS |
|---|---|---|---|---|
| **Column** | **1** | **2** | **3** | **4** |
| **Dependent variable** | **Yield (ha)** | **Yield (ha)** | **Insured^** | **Yield (ha)** |
| | (0.027) | (0.031) | (0.057) | (0.020) |
| **Soil color: Base—black^** | | | | |
| Brown^ | -0.097*** | -0.049** | 0.095* | -0.074*** |
| | (0.020) | (0.024) | (0.049) | (0.016) |
| Yellow or red^ | -0.047 | 0.059** | -0.132** | 0.000 |
| | (0.030) | (0.030) | (0.064) | (0.021) |
| Soil health card^ | -0.007 | -0.000 | 0.622*** | -0.014 |
| | (0.025) | (0.042) | (0.060) | (0.021) |
| Borrowed money^ | 0.042** | 0.083*** | 0.513*** | 0.065*** |
| | (0.020) | (0.024) | (0.043) | (0.015) |
| Number of crops cultivated | -0.027** | -0.017 | -0.077** | -0.028*** |
| | (0.013) | (0.019) | (0.031) | (0.010) |
| Number of cattle (*log*) | -0.010 | -0.007 | 0.055** | -0.011 |
| | (0.013) | (0.014) | (0.028) | (0.010) |
| Varietal age (years) (*log*) | 0.009 | 0.001 | -0.004 | 0.006 |
| | (0.006) | (0.006) | (0.012) | (0.004) |
| **Instrumental variable** | | | | |
| Bank density (Number of commercial banks in each district / area of district in square kilometre) | | | 0.123*** | |
| | | | (0.041) | |
| $\sigma_i$ | -0.759*** | -0.640*** | | |
| | (0.032) | (0.025) | | |
| $\rho_i$ | 0.076** | -0.104** | | |
| | (0.054) | (0.068) | | |
| Constant | 3.282*** | 2.852*** | -1.581*** | 3.010*** |
| | (0.091) | (0.072) | (0.154) | (0.051) |
| State fixed effect | Yes | | | Yes |
| Observations | 8,035 | 8,035 | 8,035 | 8,055 |
| R-squared | | | | 0.118 |

**Source:** Author's calculation.
**Note:** Robust standard errors in parentheses; *, **, and *** indicate statistical significance at the p < 0.1, p < 0.05, and p < 0.01 levels; ^ = binary variable; OLS = ordinary least squares.

After estimations from Table 7 of the rice yield equation from the ESR model, the next step is to calculate the expected values. Table 8 presents the expected value of rice yield under actual and counterfactual conditions; cells (a) and (b) represent the expected value of outcome variables. The expected value of rice yield for the treatment group (22.88 q/ha) was higher than for the control group (19.91 q/ha). This simple comparison, however, could be misleading in attributing the different values of rice yield to the treatment group. The second-last column of the first panel in Table 8 presents the treatment effects of the treatment group on rice yield. In the counterfactual case (c), farmers under treatment would have a rice yield that was lower by 2.97 q/ha if they had not been treated. The positive mean difference of (d) and (b) elicits a similar conclusion: control group farmers would have increased their rice yield by 1.58 q/ha if they were in the treatment group. However, the transitional heterogeneity effect of rice yield is positive, meaning that the effect would be greater for the treatment group than for the control group. Findings indicate that crop insurance promotes increased agricultural output by managing risks.

**Table 8. Treatment and heterogeneity effect**

| | Crop Insurance | No Crop Insurance | TE | Percent change |
|---|---|---|---|---|
| Crop insurance | 22.88 | 19.91 | TT=2.97*** | 14.91 |
| No crop insurance | 21.30 | 19.72 | TU=1.58*** | 8.02 |
| Base heterogeneity | 1.58 | 0.19 | TH=1.39*** | |

**Source:** Author's calculation.
**Note:** *, **, and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels; TT = the effect of the treatment (that is, farmers with crop insurance) on the treated (farmers without crop insurance); TU = the effect of the treatment (that is, insured) on the untreated (uninsured); TH = (TT − TU) (that is, transitional heterogeneity).

## 6. Conclusions and Policy Implications

Since the early 1970s, policymakers in India have tried to protect smallholders by implementing various crop insurance schemes. However, most efforts to enhance food security using crop insurance have not been very successful. With a growing population, decreasing farm size, increased budgetary pressures, and pressure to improve productivity and food security, policymakers have increasingly instituted market-oriented policies and invited greater private sector initiatives; one such effort has been the designing and selling of crop insurance to smallholders. This paper analyzes the impact of crop insurance (CI) on the food security of rice farmers in eastern India. We used large scale farm-level data from smallholder rice producers in six states of eastern India. We found CI to have a positive significant impact on rice yields of smallholders in these states and the results are robust for a variety of estimation strategies.

Clearly, crop insurance is an important risk management tool for smallholders in India. The findings have various policy implications: the fact that CI has a positive impact on rice yields means there is no strong evidence of moral hazard; thus, in the absence of moral hazard, it may be a good idea to provide a larger subsidy to CI schemes. Additionally, involving private insurance companies in the provision of crop insurance schemes could help policymakers to design policies that are efficient and productive to smallholders. The entry of large numbers of players will ultimately create competition in the market, reducing costs in the longer run. Since a large proportion of farmers are small, marginal, and medium-sized, critical barriers to broader access and availability of crop insurance still need to be addressed, including increasing efforts to sensitize these farmers as to its advantages.

There are some limitations to our study. It has identified the impact of crop insurance on rice yield, but data limitations prevented us from fully exploring the channels through which this yield improvement is occurring; we do not know, for instance, if improved yields are due to factors such as increased use of improved seeds or chemical inputs.

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