# Picture-based crop insurance: using farmers' smartphone pictures to reduce basis risk and costs of loss verification

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**Formative evaluation report**

**Accepted by 3ie: July 2020**

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## About this formative study

This formative evaluation was submitted in partial fulfilment of the requirements of grant TW13.I.1038 awarded under Agricultural Insurance Evidence Programme. This version of the report is technically sound and 3ie is making it available to the public in this final report version as it was received. No further work has been done.

The 3ie technical quality assurance team comprises Bidisha Barooah, Rosaine Yegbemey, Stuti Tripathi and Deeksha Ahuja with overall technical supervision by Marie Gaarder.

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3ie received funding for the Agricultural Insurance Evidence Programme by UK aid through the Department for International Development. A complete listing of all of 3ie's donors is available on the 3ie website.

Suggested citation: Ceballos, F, Kramer, B, Mishra, A, Robles, M and Toor, MS, 2020. *Picture-based crop insurance: using farmers' smartphone pictures to reduce basis risk and costs of loss verification*, 3ie Formative Evaluation Report. New Delhi: International Initiative for Impact Evaluation (3ie). Available at: https://doi.org/10.23846/TW13FE11

## Acknowledgements

We are grateful to Siddhesh Karekar (HDFC) for product implementation, H.S. Sidhu and Uttam Kumar (BISA) for their invaluable advice, Koen Hufkens, Michael Mann and Eli Melaas for index development, Matthew Krupoff for research assistance, and Christelle Bamona, Amandeep Chhabra, Manjinder Singh, Baldeep Singh, Yugraj Dhillon, Sarabjit Singh, Yudhisther Kumar, Dhurvinder Singh, Sukhvinder Singh, Gurtieth Singh, Lakhveer Singh, Gagandeep Singh, and Karamdeep Singh for their dedication to the fieldwork. This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). Funding support for this study was provided by the International Initiative for Impact Evaluation (3ie) and the CGIAR Research Program on Policies, Institutions, and Markets. This report has not gone through IFPRI's standard peer review procedure. The opinions expressed here belong to the authors, and do not necessarily reflect those of 3ie, PIM, IFPRI, or CGIAR.

## Summary

Millions of smallholder farmers around the world lack access to affordable insurance. Their farms are often too small and too remote for insurers to verify damage on a case-by-case basis at a reasonable cost. Take-up of existing products that can be offered affordably– such as weather index insurance and area-yield insurance—has been low due to high basis risk, poor understanding, low trust and limited tangibility. Picture-based insurance (PBI) is an innovated product that aims to deliver affordable and easy-to-understand crop insurance using farmers' smartphone pictures. By taking regular pictures using their own smartphones, farmers can reliably document damage after a natural calamity and provide evidence that the crop was managed appropriately until that point. This brings down the costs of loss verification substantially. For farmers, this approach is participatory, tangible, and can deliver plot-level assessments of damage, removing key barriers in the demand for existing index insurance products, including basis risk, trust, and understanding.

This study is a formative evaluation of PBI. The evaluation objective is to assess the feasibility and economic viability of this insurance approach. On one hand, the formative evaluation aims at assessing farmers' willingness to provide crop pictures on a regular basis through their smartphones, and the ability to assess damage from these pictures, that is, the degree to which this insurance approach reduces basis risk. On the other hand, in order to assess economic viability, the evaluation aims at measuring willingness to pay for PBI in relation to more conventional weather index-based insurance products, and at testing for supply-side impediments to scale-up such as moral hazard and adverse selection.

The evaluation was conducted in Haryana and Punjab, two states in northwest India, targeting in total 750 smallholder producers of wheat. Haryana and Punjab are the second and third largest wheat producing states in India and play a critical role in India's food grain supply. Although yields in these two states have traditionally been among the highest in the country, and although most farmers have access to irrigation, wheat yields have stagnated, and are increasingly exposed to extreme weather events including excess rains and warmer temperatures due to climate change. By reducing exposure to risk, PBI could help promote investments in productivity-enhancing technologies, especially given high smartphone penetration in these two states.

To assess feasibility, we offered 750 farmers from 50 villages an insurance product conditional on them uploading, within a smartphone application, pictures of their wheat on a regular basis, from land preparation until harvest. Further, we estimated the correlation between picture-based estimates of crop damage and objectively measured yields to assess the degree of basis risk. To test for moral hazard, we designed a cluster randomized trial in which half of the villages received weather index-based insurance (WBI) only, and the other half received WBI plus picture-based insurance (PBI) coverage for visible damage in the uploaded stream of smartphone pictures. Worse input usage, lower yields, or higher estimates of crop damage in villages with PBI coverage would be indicative of moral hazard. Finally, to measure demand and test for adverse selection, we used the BDM auction mechanism among 100 of the initial 750 farmers to elicit incentivized measures of willingness to pay for WBI versus PBI coverage in the next wheat production season.

We find that farmers are able and willing to use the smartphone application and upload enough pictures of sufficient quality for loss assessment, although technical problems in the smartphone app prevented farmers from uploading as many pictures as requested initially. Damage was nonetheless visible from smartphone pictures and could be quantified; picture-based damage estimates are strongly correlated with yields and improve upon weather-based indices. Farmers are willing to pay more for PBI than for WBI, mainly because they perceive PBI to reduce basis risk; however, demand remains below the market premium rate of the product. PBI did not induce moral hazard or adverse selection

Based on these findings, we conclude that PBI offers a promising alternative to existing insurance products for poor farmers. There is value in conducting an impact evaluation of the long-run impacts that this product can have on production decisions and human capital investments. In the formative evaluation, loss assessment was done through visual inspection of pictures, but research to automate image processing is already underway. Moving forward, the study team has improved smartphone app performance; this upcoming Rabi season the team is piloting bundling with picture-based agro-advisories to create immediate rewards for sending in pictures; and we are planning to tap into existing insurance schemes to reduce insurance premiums. Further, we will explore external validity in other states with lower smartphone penetration but higher production risk, and for other crops than wheat, including high-risk horticultural cash crops, to help promote production diversity and the scope of crops covered by agricultural insurance schemes.

# Contents

## List of figures and tables

## Abbreviations and Acronyms

| | |
|---|---|
| ANCOVA | Analysis of Covariates |
| BDM | Becker-DeGroot-Marschak |
| BISA | Borlaug Institute for South Asia |
| CCE | Crop Cutting Experiment |
| CRCT | Cluster Randomized Control Trial |
| DAP | Diammonium phosphate |
| GPS | Global Positioning System |
| HDFC | Housing Development Financial Corporation |
| IFPRI | International Food Policy Research Institute |
| ITT | Intent to Treat |
| KCC | Kisan Credit Card |
| OLS | Ordinary Least Squares |
| PBI | Picture-Based Insurance |
| PMFBY | Pradhan Mantri Fasal Bima Yojana |
| Rs | Indian Rupees |
| RWBCIS | Restructured Weather Based Crop Insurance Scheme |
| ToC | Theory of Change |
| USD | US Dollars |
| WBI | Weather Index-Based Insurance |
| WTP | Willingness to Pay |

# 1. Introduction

Farmers in India are increasingly exposed to climate change and natural disasters, causing extreme hardship. Anticipating the possibility of such calamities, farmers underinvest in productivity-enhancing technologies. Policymakers hence seek ways to improve farmers' resilience, and delivery of risk management strategies, including crop insurance, has become a major objective on policy agendas. Existing insurance products however face several challenges. On one hand, traditional indemnity insurance products suffer high transaction costs and moral hazard (Hazell, et al., 1986). On the other hand, index-based insurance, which could overcome such concerns by relying on indices that are easily measurable and outside the farmer's control, suffer low demand due to basis risk, lack of trust, and poor product ownership (Cole et al., 2013). Satellite imagery-based yield predictions offer a promising alternative, but remote satellites are intangible to farmers and the currently available (affordable) imagery is too coarse to detect damage on individual smallholder farmers' plots, especially when damage arises from localized calamities such as hail storms or excess rainfall.

This report describes findings from a formative evaluation of picture-based insurance (PBI). PBI is an innovative crop insurance product that uses geo-referenced repeat pictures of insured plots, taken by farmers using their own smartphones from land preparation to harvest, for claims settlement. Images are being processed to predict crop damage based on a farmer's own stream of crop pictures. Providing insurers with eyes on the ground, this approach could help reduce basis risk, monitor management practices to avoid paying out for damage that the farmer could have easily prevented, speed up claims processing, and improve farmer engagement. This innovation comes in a timely manner. The product builds on a trend in India of increasing smartphone ownership, improved penetration of low-cost mobile internet services among smallholder farmers, and recent advances in image processing for applications in near-surface remote sensing through digital repeat photography. Doing so, we follow a similar approach as the PhenoCam project, which monitors and quantifies canopy phenology across the northeastern United States and adjacent Canada to monitor vegetation over time through imagery from a network of digital cameras (see https://phenocam.sr.unh.edu/webcam/ and Richardson, et al., 2017). Quantitative color information is extracted from each picture, providing information about the amount of foliage present and its color, which in turn helps predict crop productivity.

In evaluating the feasibility of this approach, we focus on smallholder wheat producers in the states of Punjab and Haryana in Northern India. These states produce the second- and third-largest quantity of wheat in India, making them major actors in South Asian wheat markets. Further, these states have experienced considerable increases in smartphone ownership in recent years, providing an excellent opportunity to test newly developed insurance products that leverage farmers' existing smartphone technology. Finally, extreme weather events, a receding water table, and associated damage to crops have become an increasing burden to farmers' livelihoods. Policymakers in the two states are hence extremely interested in the development of better financial and non-financial instruments to manage risk.

Also at the national level, policymakers respond to the increasing hardship caused by natural calamities. In 2016, the central government of India launched a subsidized area-yield index-based crop insurance scheme for major crops, the Pradhan Mantri Fasal Bima Yojana (PMFBY). However, this scheme, which relies on crop cutting experiments (CCE) to measure village-level yields, suffers implementation challenges. Conducting village-level CCEs for all major crops are posing a major cost and burden to state governments, resulting in long delays in data processing and grievances regarding claims settlements. Furthermore, since most farmers are being enrolled automatically without their awareness or consent by taking out loans, awareness, product understanding and ownership are low. This has raised policymaker interest in applying new technologies, such as PBI, to reduce the costs and delays associated with the CCEs, expand coverage, and increase farmers' awareness around, and interest in, insurance.

As PBI is a novel concept that has not been tested before, this formative evaluation addresses key knowledge gaps around the feasibility of this approach. First, the evaluation provides evidence on the extent to which farmers are willing to participate in the insurance process by regularly uploading geo-referenced pictures of their plots. Second, we study to what extent damage is visible in the smartphone camera data. A prerequisite for picture-based loss detection is that the imagery contains visible characteristics that are predictive of crop damage. Although this has been documented for pictures taken through the PhenoCam network of web cameras in northern America, the question remains whether smallholder farmers, using their own smartphone cameras, are able to provide imagery of sufficiently high quality and whether findings from trials translate to the rural Indian setting. In other words, the study assesses to what extent this approach can indeed help reduce basis risk.

A second knowledge gap that is being addressed is whether PBI is viable from an economic perspective. In theory, improved farmer engagement and reduced basis risk could help improve willingness to pay, but in the absence of past studies or pilots of PBI, testing this assumption is important before refining PBI products further and implementing these products on a larger scale. Moreover, the formative evaluation analyses the costs associated with the provision of PBI, focusing on the possibility of moral hazard and adverse selection to drive premiums upwards. These information asymmetry-related problems have been considered a major barrier in the provision of traditional indemnity insurance, but the repeat nature of the pictures used for claims settlement implies that insurers have eyes on the ground even before damage occurs, allowing them to monitor whether the damaged crops were damaged properly prior to the calamity. These are important knowledge gaps that need to be addressed before developing and testing PBI products at scale.

The overarching evaluation question of the picture-based insurance project is whether the introduction of insurance products with low basis risk and high farmer engagement improves insurance uptake and is associated with stronger impacts of insurance on investments in income-enhancing technologies and practices, and whether such products can be offered sustainably. During the formative evaluation, we specifically test whether picture-based loss assessment helps improve the willingness to pay for insurance vis-à-vis the costs of providing the insurance product, and we will explore whether our findings are driven by a reduction in basis risk, an increase in trust and ownership, a reduction in the costs of loss assessments, and challenges related to adverse selection and moral hazard.

The literature has identified basis risk as a key barrier in demand for index products (Clarke 2016; Miranda & Farrin 2012; Binswanger- Mkhize 2012). Basis risk can be considerable (e.g., Clarke et. al 2012; Jensen, Barrett & Mude 2014), and reduces demand for insurance substantially (Hill, Robles & Ceballos 2016; Jensen, Mude & Barrett 2016; Karlan et al. 2014; Mobarak & Rosenzweig 2012). Our priors are that PBI reduces basis risk by assessing losses at the plot level as opposed to a distant weather station (reducing spatial basis risk); by covering visible damage, including pests and diseases, and lodging, as opposed to only weather-related events (reducing design basis risk); and by following the crop cycle instead of events at a specific point in time (reducing temporal basis risk). In this way, the product combines key advantages of index-based insurance – timely compensation without expensive loss assessments – and indemnity insurance – minimum basis risk. Demand is also hampered by distrust in insurance providers (Gine et al., 2010; Cole et al., 2013) and low product understanding (Ceballos et al., 2005). PBI is participatory, and engages the farmer in the insurance process, adding tangibility by giving the farmer power by taking the pictures himself/herself. Thus, our priors are that reduction in basis risk, and improved trust and ownership will increase demand.

On the supply-side, we study to what extent the shift away from weather index-based insurance into multi-peril insurance, which relies not on objectively verifiable weather events but on visible damage in smartphone camera pictures, gives rise to information asymmetry-related problems, including adverse selection, moral hazard, and tampering with pictures to manipulate insurance payouts. Although often considered a major barrier in the supply of multi-peril indemnity products, the extent to which these problems arise remains an empirical question, While Horowitz & Lichtenberg (1993) provide solid evidence of moral hazard, Smith & Goodwin (1996) and Babcock and Hennessy (1996) do not replicate this finding. This, combined with the fact that the high frequency of taking pictures reduces information asymmetries (allowing insurers to reduce premiums for farmers taking precautionary measures), suggests that moral hazard will remain limited. In addition, the ownership of smartphones, and the low cost of loss verification, would make PBI sustainable from a cost perspective in the long run.

Other crop insurance products have aimed to improve uptake through different approaches. For instance, products that combine insurance with drought tolerant seeds have been shown to lower basis risk, and increase uptake (Lybbert and Carter, 2013; Ward and Makhija, 2016). Another idea has been to shift focus from insuring individual farmers to insuring so-called aggregators, such as farmer associations or pregroups and microfinance institutions (see for example de Janvry, Dequiedt, and Sadoulet, 2014; Dercon et al., 2014). An institution holding a significant portfolio of agricultural loans may be interested in insuring it against severe systemic shocks that may otherwise result in large loan write-offs. The stated advantage of such a system is that individual (idiosyncratic) negative and positive basis risk could be largely offset by each other in the aggregate portfolio. Nevertheless, a prerequisite for such a scheme is that such aggregators already form part of the rural ecosystem. In addition, when aggregators receive payouts these still have to be distributed among affected farmers, which may give rise to other problems and undermine the benefits of insurance, particularly in the case of the poorest farmers.

Another proposal to minimize basis risk has been to add “gap insurance” as a second tier of *indemnity* insurance—which would kick in only if the broader index product had not triggered (Berhane et al., 2015). This system has been implemented by sending insurance verifiers to a small geographic unit to assess yields at a localized level. However, such arrangements are still costly and difficult to bring at scale. In this sense, basing insurance payouts on pictures to capture individual losses stands as a promising approach. A related idea is “multi-scale area yield insurance,” under which a product would combine two area-yield indexes measured at different geographical levels: a broader geographical index with a higher trigger and a local index with a lower trigger (Elabed et al., 2013). Payouts would happen when both indexes are below their corresponding triggers. Measuring yields at a very local level reduces basis risk, and the broader area index helps reduce moral hazard. As far as this product reduces basis risk, it does not eliminate it, and it relies on costly crop cutting experiments to calculate average yields at different geographic levels, an element that we have discussed as being an issue for PMFBY in our study context.

This formative evaluation is the first to provide empirical evidence from both demand- and supply-side perspectives for an innovative, picture-based, crop insurance product. We will add to the existing evidence of crop insurance innovations, by estimating the willingness to pay for more comprehensive coverage compared to weather index-based insurance; and by analyzing the effects this additional coverage has on production decisions.

This report is structured as follows. In the next sections, we will first describe the context in which the formative evaluation was conducted, followed by a more detailed description of the intervention and the theory of change. Section 4 provides an overview of the monitoring plan. Section 5 summarizes the evaluation questions and the primary outcomes of interest. Section 6 describes the design of the evaluation, including data and methods, followed by a description of the study timeline in Section 7. Section 8 summarizes the formative evaluation findings regarding feasibility, demand and information asymmetry problems, and in Section 9, we discuss the implications of these findings. Section 10 concludes with the major challenges and lessons learnt during the formative evaluation.

## 2. Context

### 2.1 Description of study region

The study was conducted in Haryana and Punjab, two states in northwest India. These two states are the second and third largest wheat producing states in India and the largest contributors to the central pool of food grains used to provide welfare entitlements to India’s poor. Having received major investment as the prime location for India’s “green revolution” in the 1960s, the two states have a high proportion of total cropped area under irrigation, with 99% in Punjab and 84% in Haryana (Government of India, 20160), and a high use of fertilizers and mechanization compared to the rest of India. Farmers in these states also have higher agricultural incomes and larger landholding sizes compared to the rest of India (Government of India, 2016). However, in the last decade, yield-growth has stagnated and farmers have struggled with depleted water tables and poor soil fertility (Ministry of Agriculture and Farmer’s Welfare, 2015-2016).

Like other states in the Indo-Gangetic Plains, Haryana and Punjab have started experiencing increasingly more extreme weather events due to climate change. Temperatures are on the rise and farmers are more often exposed to unseasonal rains, which both have major implications for wheat yields. The warming in recent years, and the crop losses that have resulted from this, has even been linked to a spike in farmer suicides in recent years (Carleton, 2017). Accessible irrigation networks have been effective in mitigating the risks associated with droughts, but the increased demand of water resources has resulted in extensive use of groundwater, causing a drastic decline in the water table in the region (Pandey, 2016).

In this light, it is important to evaluate whether new technologies can improve farmers' livelihoods by reducing basis risk and farmer engagement. Increasing smartphone ownership in India offers an opportunity to apply such new technologies. India has become the second largest smartphone market, with 275 million users or 24 percent of the population as of 2016; and an additional 330 million people expected to subscribe by 2020, which would amount to a penetration of 49 percent (GSMA, 2016). Within India, Punjab and Haryana are among the fastest adopters of smartphone technology; these states have experienced greater penetration of smartphones compared to the rest of India with device penetration reaching already over 50% (Enterprise Networks, 2016). Thus, smartphone ownership is much higher in our study region compared to other states.

## 2.2 Rationale for selection

This was part of the reason for conducting a formative evaluation in Haryana and Punjab. Due to high smartphone ownership and homogenous production patterns, we could find a critical mass of farmers being able to provide smartphone camera data for the same crop, facilitating a first proof of concept and providing tools and insurance products that can be further refined for operationalization in other states with increasing smartphone ownership. Further, although essential to India's wheat production, wheat yields have stagnated in recent years in these states, raising the question whether insurance can help promote yield-enhancing investments and increase productivity. Moreover, although increasingly exposed to climatic risks, farmers in these two states do not (perceive to) have access to insurance products to cope with the financial consequences. Punjab decided not to participate in the PMFBY, and awareness of the scheme was low in Haryana at the time we started the formative evaluation. Delivery of innovative risk-management strategies is hence highly relevant in both states.

The formative evaluation focused on selected villages from three districts in Punjab (Ludhiana, Fategharh Sahib, and Patiala) and three districts in Haryana (Sirsa, Fatehebad, and Yanumunagar). We selected these districts for an initial pilot because of the presence of a weather station network in these districts, with historical data being available for weather stations in nearby districts. This allowed the IFPRI-BISA-HDFC consortium to develop and implement weather index-based insurance products on which we built the picture-based insurance products. We decided to continue working in these districts as part of the formative evaluation in order to build on existing project infrastructure.

## 2.3 Current risk management strategies

In 2015/16, the Government of India introduced the Pradhan Mantri Fasal Bima Yojana (PMFBY, or Prime Minister's National Crop Insurance Scheme), a subsidized scheme to protect farmers against financial risks posed by extreme weather events, and Haryana decided to participate in the scheme. The PMFBY is based on 'area-yield' indices, meaning that payouts are triggered when the average yield measured through crop cutting experiments (CCEs) within a village drops below the historical average. The scheme is offered through voluntary enrolment; however, coverage is compulsory if a farmer takes out a loan through Kisan Credit Card (KCC) – a credit scheme for loans to promote investments in agricultural production.

Implementation of PMFBY has faced a multitude of challenges. Conducting CCEs is time-consuming and resource-intensive, creating a major cost and logistical burden for state governments and insurers. Unsurprisingly, this has led to long delays in processing CCE data and payments to farmers, and, in some states, failure to conduct CCEs altogether, resulting in major disputes about claim settlements. Indeed, in Haryana, delays in payouts have been a persistent complaint about the insurance scheme, making the scheme unpopular (Das, 2017). Take-up was less than 10% of farming households in Kharif 2016, and most uptake was compulsory as it was linked to farmers taking out KCC loans (Chandra and Kumar, 2017).

In Punjab, the government opted out of PMFBY due to low popularity amongst farmers, and a general lack of trust in the scheme. Farmers in Punjab also have low-cost access to irrigation networks, reducing concerns around catastrophic losses due to crop damage. This lack of interest arises despite Punjab's increased exposure to extreme weather events such as unseasonal rains, hail storms, lodging, and pests and diseases in recent years (The Tribune, 2016). Instead of participating in the PMFBY, Punjab provides farmers with compensation at times of natural disasters. In focus group discussions with farmers, they often express their concerns with the disaster reduction scheme, as the distribution of compensation is done by community leaders, introducing possibilities for political economy to influence which farmers receive compensation.

Alternative risk management strategies exist but are incomplete. More than 95% of farmers in our study use electric tube wells for irrigation to manage the risk of low rainfall, but excessive use has drastically reduced ground water supply. In response, efforts by state ministries are underway to encourage farmers to mitigate risks by adopting conservation agriculture (CA), which reduces the use of labour, fertilizer and irrigation, and improves wheat resilience in the face of excess rainfall and extreme heat. Current adoption amongst farmers in both states is however low because many farmers believe that CA increases rather than decreases exposure to risks (Kramer et al, 2016). Due to the perception that CA increases risk exposure, insurance and CA could be complementary, and the uptake of improved insurance products could help encourage CA adoption. Moreover, by covering actual damage instead of only adverse weather events that are not perfectly correlated with the damage experienced by farmers, PBI reduces the perceived risk of adopting CA more than weather index-based insurance. Finally, the PBI approach allows monitoring practices, and one could envisage providing insurance discounts to farmers adopting CA in order to incentivize the adoption of this risk mitigating technology. These interactions between PBI and CA were not explicitly explored in the formative evaluation but could be an area for future research.

Many farmers in Haryana and Punjab also use agricultural weather forecasts as an ex-ante risk mitigation strategy. Their forecasts come from many sources, including SMS and voice messaging, the internet, radio and television, as well as newspapers. Often, these forecasts are delivered by the Indian Meteorological Department. These forecasts are mostly used for temperature, and rainfall forecasts, but are also widely used to track the onset of monsoons, which is important for rice production in the monsoon season. Farmers have been shown to respond to these forecasts in their production decisions, with positive impacts on mean profits (Rosenzweig and Udry, 2014). Weather forecasts can be complementary to PBI, as weather information can be sent to the farmers through the app, and, perhaps more importantly, provide farmers with information on how to prevent moderate losses themselves in cases where ex-ante prevention of moderate losses is a cheaper risk management strategy than ex-post insurance. This complementarity will allow PBI to focus on compensating farmers for catastrophic damage from more severe weather events, which could not have been prevented ex ante without significantly reducing production and investments at either the intensive or extensive margin.

Although insurance coverage is low, financial inclusion is high in Punjab and Haryana. Most farmers in our sample have access to banking and credit through cooperative societies (51%), bank accounts (98%), and the Kisan Credit Card (KCC) scheme (31%). These allow farmers to access savings and liquidity to cope with losses and smooth consumption in case of an income shock. Indeed, farmers in the sample villages have coped with income shocks in previous years by drawing from their savings accounts (92%), and taking out loans (54%), but around 70% of farmers said they have also reduced large expenditures on items such as school fees and agricultural machinery. Access to credit and savings instruments has an ambiguous interaction effect with insurance. On the one hand, these financial instruments provide liquidity to help farmers smooth consumption in the case of an income shock, potentially reducing farmers' interest in, and impact of, insurance. On the other hand, financial inclusion helps relax liquidity constraints to purchase insurance, potentially increasing uptake and hence impacts. In that case, with agricultural insurance, farmers can smooth consumption without having to draw from savings, or become indebted, allowing them to continue investing through large purchases in agricultural technologies and human capital.

Finally, an additional way in which farmers tend to cope with weather shocks is by relying on their social networks to obtain informal loans or gifts. This strategy can successfully help when risk is of a more idiosyncratic nature or, in other words, when a farmer suffers a loss while his or her social network does not. The problem arises when risks are of a systemic nature, thus affecting most households in a region and reducing their ability to help each other. In this context, PBI's role as formal insurance can help improve the coping capacity of the insured farmer directly, and potentially that of his or her social network, even in a situation where only a fraction of farmers are insured.

## 3. Intervention description and the theory of change

### 3.1 Intervention

Prior to the intervention, the study team including researchers from IFPRI and BISA, practitioners from HDFC, and collaborators with expertise in geography, remote sensing and crop phenology from the George Washington University, Boston University and Harvard University (currently Ghent University), developed a novel insurance product: picture-based insurance (PBI), which pays out when there is damage visible in a stream of pictures uploaded by farmers themselves using their own smartphones.

The product also included a weather index-based insurance (WBI) component for excess rainfall and extreme heat in the period February to April. These indices were the main weather risks reported by farmers that could be measured through weather stations. They were based on focus group discussions and key informant interviews conducted during the intervention design. Weather indices were recorded at a nearby weather station within five kilometers from study villages. The trigger values were set to the 70$^{th}$ percentile based on historical weather data, exit values were set to the 99$^{th}$ percentile, and the insured sum was 13,000 Indian Rupees (Rs.) or, at the current exchange rate of Rs. 65 per USD, 200 US dollars per acre (Rs. 32,124 per hectare).

The PBI product was implemented with the facilitation of a smartphone application, WheatCam (the app was named after wheat because of the focus on this crop during the formative evaluation). This mobile application was initially developed from scratch by a programmer team in Europe, and development was taken over by a team based in India to streamline troubleshooting.

Enrolment was done as follows. In September 2016, BISA enumerators visited each village to conduct a village session with all participating farmers. In these sessions, the team explained to farmers the insurance product that farmers were going to receive, including the conditionality around taking pictures throughout the season. The explanations were aided by specially-scripted, locally-filmed videos detailing the characteristics of each product using plain, local language, and detailed insurance brochures in both Hindi and Punjabi. All enumerators were trained by IFPRI staff on the insurance products and instructed to explain one more time the products to farmers and resolve any questions or doubts they may have had.

Once enrolled, farmers were instructed to take a picture from the same site with the exact same view frame two to three times a week throughout the season from sowing to harvest. Visual aids, for instance a reference pole installed in the field, and a "phantom" image of the initial picture that was shown when taking a repeat picture, were used to ensure that the region shown in the pictures remained the same throughout the time series. Pictures were ideally taken between the hours of 10am to 2pm to standardize lighting conditions and reduce confounding shadows in the pictures, but due to software problems in the WheatCam app and the lack of a feedback system sending farmers reminders, we were forced to remove this constraint. The smartphone app uploaded the time-series of pictures onto a server for loss assessment purposes.

Loss assessments were conducted by an independent panel of six wheat experts at the end of the season. The panel included researchers from Punjab Agriculture University and Haryana Agriculture University, as well as wheat breeders from BISA. These experts assessed for every site whether there was any crop damage visible in the series of pictures, and if so, they indicated an estimate of the percentage loss, the cause of the damage, and whether damage was due to mismanagement.

For every crop site, three experts made an assessment individually. When large disagreement existed between these three assessments, the experts would jointly review the case and agree upon a final damage assessment; otherwise the median assessment across the three experts was considered for insurance payouts. Assessments were anonymous; experts could only see the crop pictures and the farmer ID, but had no access to the farmer's personal details, their insurance coverage, weather data, or any other characteristics.

For farmers with more than 20 percent of assessed damage, a damage report, including the pictures and expert loss assessments, was sent to HDFC, the project partner underwriting the insurance product. The payments were then issued directly into the farmers' bank accounts. Farmers with 20-50 percent of assessed damage received Rs. 3,900; farmers with 50-75 percent of assessed damage received Rs. 7,800; and farmers with more than 75 percent damage received Rs. 13,000. In case of payouts from the WBI component, farmers received the payout for the index that yielded the maximum payout. For those farmers who were eligible for claims, all documents and bank account information required by HDFC were collected by the BISA team for the subsequent issuance of payouts.

## 3.2 Theory of change

Our initial theory of change (ToC) recognizes impact pathways that link components of PBI and outputs to desired outcomes and impacts on farmers' wellbeing. Figure 1 illustrates these outputs and impact pathways. Different assumptions are stated along the impact pathway, from the intervention to positive impact on insurance uptake and farmer's wellbeing. Key assumptions motivating the hypothesis that demand for PBI coverage will be higher than demand for stand-alone WBI insurance are the following:

*Assumption (1):* Crop damage can be estimated from images with higher accuracy than from other indices used in index-based insurance, for instance adverse weather events (weather index-based insurance) and the average yield in a sub-district (area-yield insurance). Further, the detail visible in smartphone images, but not in much coarser satellite images, yields more precise estimates of crop damage, even though smartphone pictures do not yield measures of NDVI.

> *Input:* Insurance pay-outs depend on picture-based loss assessment.
>
> *Output*: Picture-based loss assessment improves the correlation between the index and yield losses compared to these other types of products.

*Assumption (2):* Ownership, trust and understanding is low for standard forms of index-based insurance.

> *Inputs:* Farmers take the pictures used for loss assessment themselves. Local experts and farmer representatives assess damage for wheat crop images, which are then used as input in machine learning to derive an algorithm that maps images into an index of crop damage.
>
> *Output:* Ownership, trust and understanding is higher for the PBI product compared to other index-based insurance products.

In a series of 12 focus group discussions involving in total more than 70 wheat growers from Haryana and Punjab, participants said they were very interested in an insurance product that pays them based on loss estimates coming from their own plots' pictures, rather than relying on distant measures such as weather indices.

*Assumption (3):* Most farmers have a smartphone with data plan, camera and GPS functionality.

*Input:* A smartphone app helps take photos from the same plot every few days and sends the photos to the insurance company for loss assessment. Fast enough image processing to yield crop damage indices in a timely manner.

*Output:* Low costs of quick loss verification that allows for timely pay-outs.

*Assumption (4):* Production decisions can be monitored using the time-series of pictures that farmers take themselves, and insurance providers can further look for moral hazard at a more aggregated level by comparing outcomes for insured plots with those of other farmers in the same locality and with uninsured plots (using for instance satellite imagery).

*Input:* Monitoring of practices and technologies in insured plots through the pictures; that is, a reduction of asymmetric information regarding production decisions.

*Output:* Farmers feel like they are being monitored, discouraging them from underinvesting in insured plots (i.e. limiting moral hazard). The insurance company can lower the premium for farmers adopting yield-increasing or risk-mitigating practices.

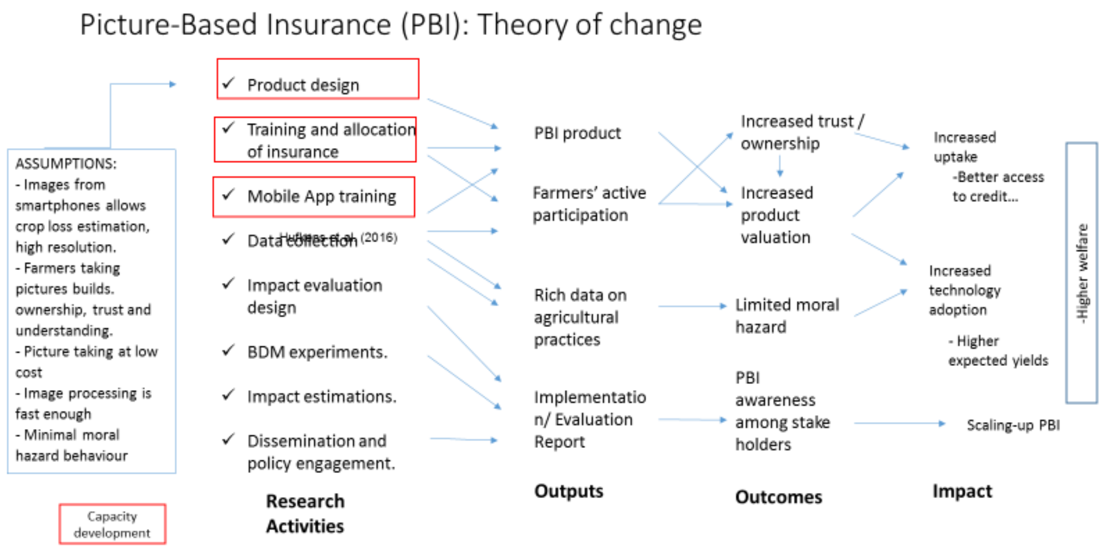
If high basis risk and a lack of trust, ownership and understanding are indeed the two main factors explaining low willingness to pay for existing index-based insurance products, then the inputs under the first two points (picture-based loss assessment based on pictures that farmers take themselves) can improve the demand for crop insurance. Key assumptions that need to be satisfied to generate higher uptake of PBI compared to stand-alone WBI insurance are (i) that farmers are not too liquidity-constrained to purchase insurance; and (iii) that PBI is not too expensive compared to WBI insurance.

Regarding this last point, supply-side considerations become critical. Under Assumption (3), loss verification is not expensive, and under Assumption (4), moral hazard will not substantially increase costs. In that way, the costs of a PBI product do not need to be too much higher than a WBI insurance product; in the most extreme case, whereby visible damage is mainly driven by weather risk and WBI is not subject to any basis risk, the two products would nearly cost the same. Our key outcomes, then, are an increased demand for PBI and an increased willingness among private insurance providers to offer insurance to smallholder farmers at affordable premiums.

The desired impact of the study is to generate higher uptake of crop insurance among smallholder farmers that offers more effective coverage against production risks. Once farmers perceive effective protection against risks, including any perceived risks associated with adopting yield-increasing or risk-mitigating practices and technologies, they are more likely to adopt such welfare-enhancing technologies. Further, as a side effect of being insured, farmers will be able to access more credit or better credit conditions, which may further improve adoption of sustainable risk management strategies. Ultimately, this will increase incomes as well as the ability to smooth consumption, resulting in improved well-being among farmers.

In the short run, moving from intangible indices measured from e.g. a distant weather station or satellite to a more tangible product based on pictures that farmers take themselves, and stronger correlation between insurance payouts and actual damage, can improve insurance uptake at affordable premiums. By bundling the advantages of index insurance – compensating farmers timely, without expensive visits to verify losses – and indemnity insurance – compensate in case of actual damage, minimizing basis risk, the product may over time help improve adoption of sustainable risk management practices and technologies that farmers perceive to be risky (although these practices mitigate risks in agronomic trials), improve access to credit, and invest in high-yielding practices and technologies. Ultimately, in the long run, we envisage this to increase incomes and smooth consumption in the presence of climatic and non-climatic risks, improving smallholder farmers' wellbeing.

**Figure 1: Theory of Change**




# 4. Monitoring plan

Table 1 summarizes the relevant input, output, and outcome indicators used to monitor the intervention. Key input indicators included the number of farmers with a smartphone, the frequency and quantity of pictures that farmers took during the study; different measures of crop yields, and crop damage assessments. Key output indicators included correlations between indices and yields; ownership, trust, and understanding of the product; participation in the picture-taking protocols; costs of loss verification; and differences in assessed losses between insured and uninsured plots. Finally, our main outcome indicators included the incremental willingness to pay for PBI and the incremental cost of providing PBI.

**Table 1: Monitoring Plan**

| Assumption | Input indicators | Output indicators | Outcome indicators |
| --- | --- | --- | --- |
| 1. Crop damage can be estimated from images with higher accuracy than from other indices used in index-based insurance | Picture-based loss assessments<br>Weather-based index<br>Individual yield | Correlation between different indices and individual yield (indicating the 'accuracy' of the index or the opposite of the basis risk) | Incremental willingness to pay for picture-based insurance |
| 2. Ownership, trust and understanding is low for standard forms of index-based insurance. | Farmers take pictures themselves<br>Local experts assess damage<br>Farmer representatives monitor the procedure | Ownership of the product<br>Trust in the product<br>Understanding of the product | |
| 3. Most farmers have a smartphone with data plan, camera and GPS functionality. | Number of farmers with smartphone (incl. camera and GPS)<br>Number of farmers with data plan<br>Number of farmers with smartphone app installed successfully | Number of farmers able to take pictures<br>Frequency at which farmers take pictures<br>Number of pictures uploaded to the cloud<br>Costs of loss verification (in R tool)<br>Time that it takes to do loss verification (in R tool) | Incremental cost of providing picture-based insurance |
| 4. Insurance providers can detect moral hazard from pictures or from comparing insured and uninsured plots | Yields<br>Assessed losses not due to mismanagement from different experts<br>Assessed losses due to mismanagement from different experts | Difference in assessed losses (not due and due to mismanagement) between insured vs. uninsured plots<br>Correlation between assessed losses (not due and due to mismanagement) across different experts, and with yields | |

Table 2 describes the source and mode of data collection for each of the relevant indicators. Focus groups at baseline provided information that was important in finalizing the insurance product design. The village census and baseline survey provided the study team with information on the number of farmers with smartphone cameras, GPS, and data plans. We planned on installing the smartphone application on farmers' smartphones during village sessions, and afterwards, to measure participation through the number of repeat pictures that a farmer uploaded through the smartphone application. Yields and damage were measured using crop cutting experiments and expert loss assessments. Ownership, trust, and understanding of the product were measured during an endline survey. Focus group discussions were used to collect qualitative data on ownership, trust and understanding.

**Table 2: Sources of Data Collection**

| **Data source** | **Mode** | **Indicators** | | |
|---|---|---|---|---|
| | | **Inputs** | **Outputs** | **Outcomes** |
| Focus groups baseline | Primary (qual) | Weather-based index | | |
| Village census | Secondary (quant) | Number of farmers with smartphone (incl. camera and GPS) | | |
| Baseline survey | Primary (quant) | Number of farmers with data plan | | |
| Village sessions | Primary (quant) | Number of farmers with smartphone app installed successfully | | |
| Repeat pictures | Primary (quant) | Farmers take pictures themselves | Number of farmers able to take pictures<br>Frequency at which farmers take pictures<br>Number of pictures uploaded to the cloud | |
| Crop cutting experiments | Primary (quant) | Area-yield index<br>Individual yield | Correlation between different indices and individual yield | Incremental cost of providing picture-based insurance |
| Expert loss assessments | Primary (quant) | Local experts assess damage<br>Farmer representatives monitor the procedure<br>Picture-based loss assessments (not due to mismanagement and due to mismanagement) by 3+ experts | Correlation between picture-based index and individual yield<br>Difference in assessed losses (not due and due to mismanagement) between insured vs. uninsured plots, and correlation across different experts | |
| Endline survey | Primary (quant) | | Ownership of the product<br>Trust in the product<br>Understanding of the product | |
| Willingness to pay | Primary (quant) | | | Incremental willingness to pay for picture-based insurance |

| Data source | Mode | Indicators | | |
|---|---|---|---|---|
| | | Inputs | Outputs | Outcomes |
| Focus groups endline | Primary (qual) | | Ownership of the product<br>Trust in the product<br>Understanding of the product | |
| Weather data | Secondary (quant) | Weather-based index | Correlation between weather-based index and individual yield | |

A number of safeguards were implemented to ensure quality of data collected. First, the data were collected by a small team of 5-8 research assistants, with multi-day trainings provided for each study activity by the PIs. Second, CAPI tools were used for the village census, baseline survey, WheatCam app, endline survey and willingness to pay study, with built-in skipping patterns and validation checks to identify any survey responses that were out-of-range or inconsistent with previous answers. Third, the CAPI tools also allowed for mobile data collection, enabling us to provide continuous feedback and where needed additional training. Fourth, with regards to crop cutting experiments and expert loss assessments, we collected two and three measures for every site, respectively, and monitored the correlation across different measurements for the same site in order to assess data quality. Finally, the field staff were closely supervised by the co-PI based in Ludhiana.

The monitoring indicators are used to track input and output indicators in the theory of change as follows. An important driver of our first outcome, the incremental willingness to pay for PBI, is the assumption that crop damage can be estimated from images with higher accuracy than from weather data. To this end, we will correlate individual yields with insurance payouts based on visible damage in crop damage versus weather indices. These inputs allow us to test whether the correlation between PBI payouts and yields is higher than the correlation between WBI and yields. A second assumption is that ownership, trust, and understanding is low for standard forms of index-based insurance, and that PBI can help improve these variables by relying on farmers' self-provided camera data and loss assessments, conducted by independent local experts, during which farmer representatives can monitor the transparency and objectivity of the procedures. We will track these indicators to assess whether this is indeed the case.

The second outcome is that the incremental cost of providing PBI is low. An important assumption underlying this outcome is that most farmers have a smartphone with a data plan, camera, and GPS functionality. To validate this assumption, we track the number of farmers who are able to provide camera data through the smartphone app, the frequency at which they provide this data, the number of pictures uploaded, and the cost of loss verification. A final assumption is that insurance providers can detect moral hazard. To verify whether this is indeed the case, we measure differences in input use, yields and loss assessments between farmers randomly assigned to receive only weather index-based insurance coverage (WBI), versus farmers randomly assigned to receive both WBI and picture-based insurance coverage (PBI). Worse input use, lower yields, or higher estimates of damage for PBI farmers is indicative of moral hazard.

## 5. Evaluation questions and primary outcomes

The main objective of the formative evaluation was to assess the feasibility and the economic viability of picture-based insurance. Our main evaluation question to assess economic viability, then, is whether PBI increases demand for insurance by improving product tangibility, trust, understanding, and product ownership, and by lowering the degree of basis risk that hampers take-up of existing alternatives. In order to answer this question, we elicited incentivized measures of farmers' willingness to pay for PBI, as well as farmers' perceptions of the PBI product in order to understand the drivers of demand.

A second evaluation question is whether farmers covered by PBI strategically underinvest in risk-mitigating practices on insured plots, and to what extent such moral hazard affects product cost. To answer this question, we tested whether PBI lowers the self-reported use of fertilizers, pesticides, herbicides, and farm labour; and whether PBI coverage was associated with more damage (visible in the pictures) of insured crops.

A third evaluation question relates to the feasibility of picture-based insurance: are farmers willing and able to take and upload the smartphone pictures, and to what extent is damage visible in the resulting stream of smartphone pictures? To study this practical feasibility, we monitored the number of farmers uploading pictures, the number of pictures uploaded to the server, farmers' perceptions on the types of damage that are visible, and the correlation between expert assessments of damage and objectively measured yields.

As such, primary outcomes during this formative evaluation included the willingness to pay for picture-based insurance versus weather index-based insurance, as well as the costs of providing the two types of insurance products. In comparing the costs of providing the two products, we were particularly interested in whether picture-based insurance coverage provides farmers with disincentives to manage their crops well, that is, whether it induces moral hazard, and whether it creates incentives to tamper with pictures in order to attract insurance payouts.

## 6. Evaluation design, data and methods

### 6.1 Qualitative Research

Focus group discussions were conducted in Punjab and Haryana during the intervention design stage to gather qualitative data on the main risks that farmers face, along with their perceptions of and overall interest in PBI. Two consultants were hired to carry out focus groups in 12 villages in both states. Part of the consultants' responsibilities was to identify six villages in their respective state with sufficient geographic and agro-ecological representativeness. Groups of between 5 and 12 farmers in these villages were selected through convenience sampling. The consultants were trained in how to conduct the focus groups, aided by a discussion guide that was provided to them with specific questions around different topics to fill out. The 12 discussions provided the basis around which to design the intervention, providing valuable information in terms of crop and risk calendars, coping mechanisms around risks, and the perceived advantages and disadvantages of linking insurance to smartphone pictures instead of, for instance, weather indices or satellite imagery. The qualitative data collected during these sessions also served as a guide to design the weather-index based product to cover the most salient risks of unseasonal rainfall and high temperatures from February to April.

Towards the end of the wheat growing season, in February 2017, another series of focus group discussions was conducted in a subsample of four study villages in Punjab, again through convenience sampling. This time, the focus group discussions were conducted by the BISA team. These focus group discussions aimed to assess farmers' perceptions and experience with the smartphone application and their perceptions around the insurance product. This included discussions on existing challenges in using the smartphone application and areas for improvement, as well as farmers' expectations of the conditions under which they would receive insurance payouts, and the types of crops to be covered through the picture-based insurance product beyond wheat.

## 6.2 Quantitative Research

We conducted a quantitative study with more than 700 farmers from 50 villages in six districts in the states of Haryana and Punjab: Fatehgarh, Ludhiana, and Patiala in Punjab; and Fatehabad, Sirsa, and Yamunanagar in Haryana, to assess the feasibility of offering picture-based insurance. For this, the study provided farmers with a free insurance product to cover one acre of their Rabi (winter season) wheat crop. Additionally, farmers were told that insurance was conditional on them taking repeat pictures of one section of their insured plot using the Wheatcam app throughout the entire season. As an encouragement to take and upload weekly pictures all farmers were informed they would receive a 2GB monthly data plan directly loaded on their phone until the end of the Rabi season. Even though the initial plan was for farmers to use their own smartphones to take pictures, compatibility problems with the app forced the study to provide basic Android smartphones to participating farmers, which served as additional encouragement.

The study was conducted across 50 villages in the states of Punjab and Haryana. In order to limit spatial basis risk in weather data, the sample frame included villages within five kilometres from one of the 25 weather stations for which HDFC would be able to source weather data. Villages were included in the sampling frame only if one of the following criteria was met: the village had at least 40 households, a total population over 140, or at least 40 main cultivators. These criteria were put into place in order to capture enough farming households to be part of the sample, and data were drawn from the 2011 Indian Agricultural Census. For every weather station, two villages conforming to the above criteria were randomly selected, resulting in a total of 50 villages (see Appendix 1 for a summary table of characteristics of the selected villages).

In each of these 50 villages, we conducted a village census of all farming households and subsequently selected 15 farmers per village, randomly, conditional on meeting the following criteria: (1) having less than 15 acres of operational farmland and (2) planning to grow at least two acres of wheat during the upcoming Rabi season. In this way, we focused on small-scale farmers. We further oversampled relatively smaller farmers by sampling an equal number of farmers with 0 to 5, 5 to 10, and 10 to 15 acres of operational farmland. Our focus on relatively smaller farmers was motivated by external validity considerations for the sample to be more comparable to the representative farmer population in other states.

The 15 randomly-selected farmers per village were asked to complete a baseline survey during July and August 2016 eliciting information on a wide range of topics such as demographic characteristics, household profile, farming knowledge and practices, output and input use from past seasons, risk exposure and coping mechanisms, past experience with shocks and insurance, and perceptions and expectations using lab-in-the-field elicitation experiments. Next, 592 farmers (approximately 12 per village) agreed to provide crop pictures on a regular basis through the smartphone app throughout the Rabi wheat season, and received a reference pole to place in the field as a visual aid to ensure pictures were always taken from the same location with the same view frame. The BISA team continued to provide support to the farmers regarding the app and any other issues the farmer would face throughout the entire season. After each repeat picture, a short questionnaire was administered through the app, capturing information about damages in the crop after the previous picture taken, the current visible and overall health of the crop, and farming practices conducted and inputs used since the last picture.

In order to test whether assessment of damage from the pictures correlated with objectively measured yields, we conducted crop cutting experiments (CCEs) in farmers' plots. For each plot, wheat heads were collected for two separate square meters in the plot: one to the left of the reference pole and one to the right of the reference pole. The heads of the wheat plants falling inside these sampled square meters were threshed, the resulting grains were weighted, and the average weight from these two square meters was used to calculate yields per acre.

An endline survey was conducted during April and May 2017 inquiring about farming practices, hazards faced, inputs used, and output obtained from the wheat crop during the season, together with farmer perceptions and understanding of the insurance products, their picture-taking activity throughout the season, and additional feedback on other topics such as usage of the smartphone application. Finally, we elicited willingness to pay for different types of insurance products prior to the Rabi 2017/18 season.

These data were used to address our key outcomes as follows.

## 6.3 Primary research objectives

### *6.3.1 Feasibility study*

To assess the feasibility of PBI, in terms of whether farmers are willing and able to take crop pictures for loss verification, we rely on administrative records around farmers' activity in terms of pictures taken, timing of the repeat pictures, quality of the images and compliance with the protocol asked from them, and number of active farmers in the study throughout the Rabi season.

To evaluate the extent to which damage assessments based on these pictures are correlated with actual yields we compared the loss assessments carried out by experts based on the time-series of pictures taken by each farmer with the objective wheat yields obtained from the CCEs at the end of the season.

### *6.3.2 Moral hazard*

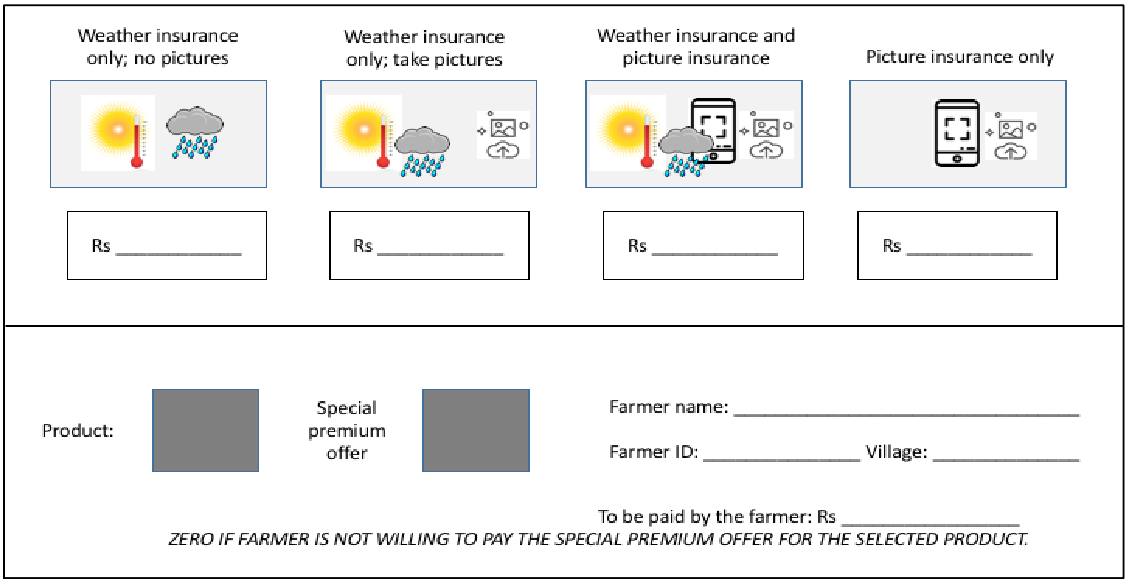
As a key outcome indicator, we wish to see if there is any evidence of moral hazard among farmers insured with PBI. To provide insights on the incidence of moral hazard, the study was designed as a randomized controlled trial (RCT) with two treatment arms. Farmers in the first arm, the control group, were provided with a free weather-index based (WBI) insurance product to cover one acre of their Rabi (winter season) wheat crop. Additionally, farmers were told that insurance was conditional on them taking repeat pictures of one section of their insured plot using the Wheatcam app throughout the entire season. Farmers in the second arm, the treatment group, were also provided with WBI and asked to take repeat pictures of their plot throughout the Rabi season. In addition, however, these farmers were informed they would receive free coverage through a new Picture-Based Insurance (PBI) product, which would pay according to the crop losses visible from the pictures they had taken. Treatment assignment was stratified by weather station.

This cluster randomized trial allowed us to compare production decisions regarding input uses between groups to test whether added PBI coverage induced farmers to apply less fertilizers, pesticides, herbicides, and labor. We also compare the expert loss assessments in the two treatment arms. Since farmers from both treatment group and control group were asked to take pictures, we were also able to predict, for the WBI treatment arm, what their insurance pay-outs would have been if they had been offered PBI. We compared estimated damage (both self-reported and objectively measured from crop cutting) as well as predicted PBI pay-outs. When there is moral hazard, estimated damage and hence predicted PBI pay-outs will be substantially higher in the PBI treatment than in the WBI treatment.

### *6.3.3 Willingness to pay (WTP)*

To elicit WTP for different types of insurance coverage during the Rabi 2017/18 season, we used the Becker-DeGroot-Marschak (BDM) method. Specifically, each farmer received a scratch card (see Figure 2 for an example) with illustrations of each product and–hidden under metallic scratch-off ink–a randomly assigned premium offer for a randomly selected product (e.g. Rs. 1,800 for WBI + PBI, in Figure 2). Farmers were instructed to write their maximum willingness to pay for each of the four products in the top panel before scratching off the ink to reveal the special offer. If a farmer's willingness to pay for the selected product was at or above the premium offer, he would purchase the product at that premium. Otherwise, the farmer would not be able to purchase any of the products at that time. This gave farmers incentives to reveal their maximum willingness to pay, as writing down a lower amount could result in them losing out on a lower special premium and as stating a higher amount could result in them having to purchase a product at a premium that they were unwilling to pay.

**Figure 2: Willingness to Pay Scratch Card**




The randomized premium offers were introduced as a special promotion to show our gratitude for farmers' active study participation during the Rabi 2016/17 season. Hence, we selected for this component the 20 villages in which farmers participated most actively, and from each village, we targeted the five most active farmers as respondents. One might worry about the selection bias that this sampling strategy could introduce. However, we found very limited correlation between willingness to pay for PBI in the Rabi 2017/18 season and either the number of pictures taken by a farmer in the Rabi 2016/17 season or the rank of a farmer within his village, indicating that selection bias is not a major concern.

Respondents were asked about their WTP for four products:

- **WBI only**: offering coverage against excess rainfall and above- normal temperatures, without having to take crop pictures.
- **WBI + pictures**: the WBI product, but paying out only if the farmer regularly takes pictures of the insured plot.
- **WBI + PBI**: the same product as WBI + pictures, but providing additional coverage against damage visible in the pictures.
- **PBI only**: covering only against damage visible in the pictures.

This design allows us to analyze several aspects of the demand for these products. One of our primary outcomes is the difference in willingness to pay between *WBI only* and *WBI + PBI*, which indicates how much farmers are willing to pay for extra PBI coverage. Other comparisons provide further insights regarding farmers' perception of these products. The comparison of *WBI + pictures* and *WBI only* reveals farmers' utility (or disutility) derived from having to take pictures regularly, providing an objective valuation of this implicit condition for receiving payouts from the PBI component. Comparing *WBI + pictures* and *WBI + PBI* quantifies farmers' valuation of picture-based loss assessment conditional on taking pictures regularly; comparing *WBI + PBI* and *PBI only* indicates how much farmers value WBI coverage and whether demand for WBI + PBI could be enhanced by reducing or removing WBI coverage.

Farmers described their willingness to pay for a product that would cover one acre of Rabi wheat, and they had the freedom to choose which one plot to insure. By providing the farmer with this choice, we can compare the characteristics of plots that the farmer chose to enroll and plots that the farmer did not choose to enroll. These analyses provide information on the degree of adverse selection; that is, whether farmers selectively enrolled plots with an in- creased risk of damage, and hence increased chance for insurance pay-outs - for instance, plots poor access to irrigation or with poor soil quality. We will also test whether the amount that farmers are willing to pay extra for *WBI + PBI* compared with *WBI only* is higher for farmers whose crops are more likely to incur damage.

## 6.4 Quality control and measures taken to ensure ethical research

In order to ensure that the data we collected was of highest quality, multi-day trainings were administered for each round by the principal investigators. Further, computer-assisted interviewing allowed for frequent validity check of the surveys that were uploaded via tablets. This allowed us to provide timely feedback and training to the enumeration team, and ensure that information was consistent and complete. Tablets also allowed us to monitor effort by automatically recording the average amount of time it took team members to complete each survey. To further ensure the highest standard of data collection, the team itself was small, well educated, and supervised by senior staff at our local implementation partners at BISA.

To ensure that the research was conducted in an ethical manner, IRB approval was obtained from the International Food Policy Research Institute (IFPRI), and all staff working on the project underwent ethics training. Participation in the study was on a voluntary basis and all farmers received accurate information on what their participation would entail before providing their formal participation consent. Consent was gathered at different stages: at baseline, when installing and explaining the photo app, and during the distribution of the insurance products.

There was no expected downside for farmers as a result of their participation in the study. On the contrary, participation could bring more than one tangible benefit to them:

- Insurance products were distributed free of charge to farmers and in the case of losses there was a high chance that they would get a sizeable compensation for their acres covered
- All farmers received an App on their phones for free. Every three days until the end of Rabi season farmers would take a photo of two different sites and answer only few questions about these photos. This process was expected to take less than 5 minutes.
- As long as farmers complied with regularly taking photos with the App, the study provided them with a monthly mobile 2GB data plan that after sending the photos could use for their personal use.
- Farmers without smartphones received a new smartphone. We provided smartphones in order to not discriminate against smallholder farmers with fewer than 5 acres, who are less likely than the larger farmers to have a smartphone.
- All farmers were invited to an information workshop where they learned more about risk management strategies and the benefits of adopting them. We organized these trainings so that a lack of awareness or knowledge was not a constraint to adoption of these practices.

All data collected was used solely for research purposes and no private information was released to third parties or in any way that could be used without explicit authorization from participants. In particular, we want to stress here that the pictures were released to the insurance provider for only the farmers who submitted a claim. Moreover, in that case, we only shared pictures and not any other data, with the insurance company. The experts and farmers who objectively assessed losses looked at anonymized series of pictures and could not see the farmer's name nor village, in order to make the loss assessment panels as transparent as possible. Farmers were informed and sensitized about this. We devoted substantial time to explain the data sharing arrangements in the consent procedure when distributing the insurance products.

## 7. Study timeline

a.) Insurance product design. From October of 2015 to March 2016, IFPRI, BISA and HDFC Ergo Insurance designed the PBI and WIB insurance products for farmers in the states of Punjab and Haryana. After formal review and evaluation procedures within HDFC Ergo and their approval to further develop and underwrite the products, the project partners jointly designed the final products. This involved specifying aspects such as cover period, risks, indices, triggers, pay-outs, claim processes, premium estimation, and selection of reference weather stations. A smartphone application was developed to collect pictures of insured plots periodically (every 3 days), which served as the basis for visual loss determination in the picture-based insurance product. For research purposes, farmers who received WIB insurance also took pictures with this smartphone application, but the pictures did not serve as a basis for loss determination.

b.) Formative evaluation design. From October 2015 to March 2016, the consortium designed the formative evaluation including methodology to assess feasibility, to identify moral hazard and to elicit the willingness to pay, and survey questionnaires were developed.

c.) Sampling. Sampling of the 50 villages and the listing exercise (census) that identified all eligible farmers was conducted in June of 2016.

d.) Baseline survey. A baseline survey was conducted in July and August 2016.

e.) Implementation. In September 2016, study farmers were invited to training sessions on agricultural risk management, in which they were introduced to the insurance products. Here, they downloaded the app, and were given information about the picture-taking protocols. Although the smartphone app was designed to be very intuitive, user-friendly, self-explanatory and easy to understand for a farmer with basic literacy skills, we trained all participant farmers on how to use the smartphone app. From November 2016 to March 2017, farmers uploaded the smartphone camera data and in March 2017, prior to harvest, objective yields were measured through crop cutting experiments. In April 2017, agronomic experts inspected for each site the stream of pictures for visible damage. In May and June 2017, we used these data along with weather data to file claims, and for farmers with claims, we collected their bank account information along with other documents requested by the insurance company. Claims were submitted to and processed by HDFC in June, processed by HDFC in July, and farmers were paid according to their claim in August. We expect this process to move faster in the future by having experts review claims from farmers as they come in;

collecting bank information and other documents already upon enrollment; and leveraging experience within HDFC with the picture-based loss assessment procedures.

f.) Endline survey. The endline survey was implemented in April and May 2017. The survey collected socio-economic information, production and agricultural practices and attitudes toward risk and insurance.

e.) BDM experiments. We measured willingness to pay in July 2017. The Becker–DeGroot–Marschak (BDM) incentive-compatible procedure was used to elicit farmers' willingness to pay for the WIB and PBI product. Willingness to pay was elicited for the next winter season, so that participants were experienced with the picture-based insurance product and the protocols for taking pictures.

f.) Formative stage impact estimations. Between June and August 2017, we quantified the effect of having picture-based insurance (PBI) over standard weather index-based (WBI) insurance on production decisions, yields, and crop damage, the effect of PBI coverage on willingness to pay for insurance, and we quantified basis risk for both PBI and WBI.

g.) Dissemination and policy engagement. We met with the Commissioners of Agriculture in Punjab and Haryana prior to the start of the formative evaluation. They expressed their interest in the study outcomes and we will continue our conversations with them. During the final project stage, we again met with the departments of Agriculture, and organized a stakeholder workshop in India on September 6th 2017. We further organized a policy workshop in December 2016 with participation of authorities of the national insurance program Pradhan Mantri Fasal Bima Yojana (PMFBY), other relevant authorities from National and State governments, and insurers' management teams.

# 8. Findings from the evaluation

## 8.1 Outcome 1: Uptake of PBI

As a first step, in this formative stage, the study team monitored whether farmers can provide inputs for picture-based loss assessments themselves by uploading smartphone pictures on a regular basis. The percentage of farmers uploading their crop pictures is also an indication of uptake, given that there was an effort involved in going to the field, taking a picture, and uploading it through the smartphone app. However, as a potentially stronger predictor of uptake and product valuation, we will also be analyzing the willingness to pay for WBI versus PBI.

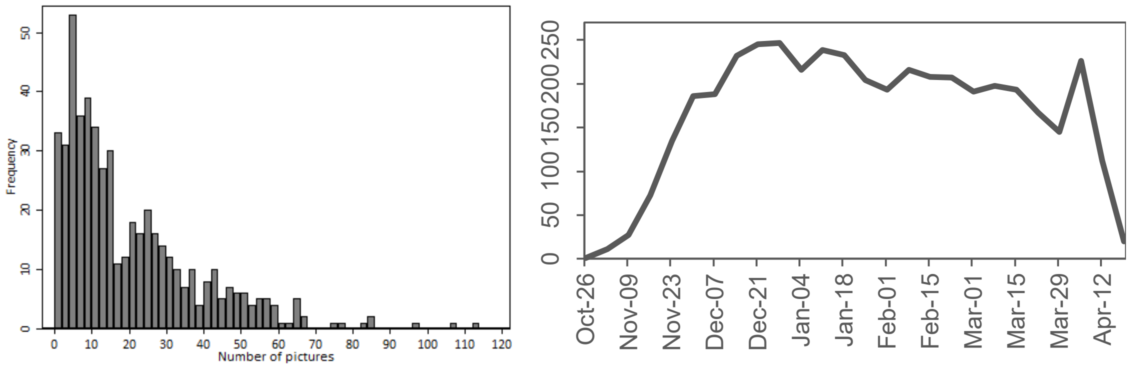
### *8.1.1 Approach 1: Did farmers take pictures in order to maintain their insurance coverage?*

The app through which farmers had to send in their pictures came with a number of challenges. There were no reminders built into the app, and there was no direct feedback system to alert farmers that there were no pictures being sent. Early in the season, farmers often could not take a picture because of GPS restrictions that were imposed to prevent tampering. Frequent crashes at initial versions were also a constant challenge during this time, especially on phones with older versions of Android, or without the right version of Google Play Services. As a result, only farmers receiving a new smartphone from the project were able to install WheatCam and start taking pictures. In the focus groups, farmers reported that these technical problems were the main reasons for not taking more pictures. These issues were overcome in later versions of the app, and we now have a smartphone app that has been tested successfully on different versions of Android and different devices, but we were unable to resolve all issues during the Rabi 2016/17 season itself, which is why we changed the criteria to qualify for a loss assessment to submitting at least 2 pictures in 2017.

Despite these challenges, we found promising levels of farmer participation. Out of the full sample of 592 farmers who after the baseline survey agreed to send in pictures on a regular basis and were trained on using the smartphone app, 475 farmers (80.2 percent) uploaded at least one valid picture during the season. Figure 3 panel A shows the distribution of the number of pictures taken. Of the farmers who took pictures, the large majority (more than 83 percent) took at least six pictures throughout the season—or roughly one picture per month—while more than 59 percent of them took pictures twice a month or more, resulting in a high-quality time series of pictures that are being used for index development.

**Figure 3: Picture-taking Activities**

A. Number of pictures taken by farmer B. Nr. farmers with at least 1 picture by week




Panel B presents the number of farmers who took at least one picture in a given calendar week throughout the season. The pattern is encouraging, with sustained submissions from an average of 200 farmers weekly, except for the beginning of the season (when the wheat plants had not started growing yet and when farmers were facing technical challenges with the app) and the post-harvest period (when farmers no longer had to take pictures). Thus, while farmers did not strictly follow the requested protocol, in part because of implementation challenges, they were able to submit a substantial number of pictures for loss assessment. Of the sample of farmers who uploaded at least one valid picture over the season, 80.5% uploaded 2 or more pictures in 2017, and were eligible for loss assessments (see Table 4).

The farmers were incentivized to take pictures through the provision of data plans, smartphones and insurance coverage. Those in the treatment group had WBI + PBI coverage, whereas the control group only had WBI coverage conditional on taking pictures. There may be a concern then that without PBI coverage, the control group had less of an incentive to take pictures than those in the treatment group, which could have reduced uptake in the control group compared to uptake in the treatment group, meaning that the findings presented earlier—based on the full sample instead of farmers in only the WBI + PBI treatment group—underestimate uptake. However, we find no evidence of this effect: the rate of farmers taking at least two pictures in treatment and control are very similar to each other and even higher for the control group (see Table 4; higher rates in the control group are driven by a handing out—unintendingly—a higher number of smartphones in these villages, and farmers without new smartphone being unable to install the smartphone app). In addition, we find that conditional on taking at least two pictures, the number of pictures taken across the entire season by treatment and control farmers follows the same pattern.

The similarity across treatment and control in the number of pictures sent conditional on enrolling in WheatCam in WBI versus WBI + PBI villages could mean two things. First, farmers may not have valued the WBI + PBI product more than the WBI + pictures product, a hypothesis that we test below by comparing incentivized willingness to pay measures for WBI only versus WBI + PBI, as a better proxy for product valuation. Second, the data plan and smartphones may have been more salient incentives to send in pictures on a regular basis. This could raise the concern that farmers may not have sent in pictures in the absence of those incentives. To assess whether this concern is warranted, we will also test whether conditioning insurance coverage on having to send pictures regularly reduces willingness to pay and hence product uptake.

#### *8.1.2 Approach 2: Differences in willingness to pay (WTP) for WBI versus PBI*

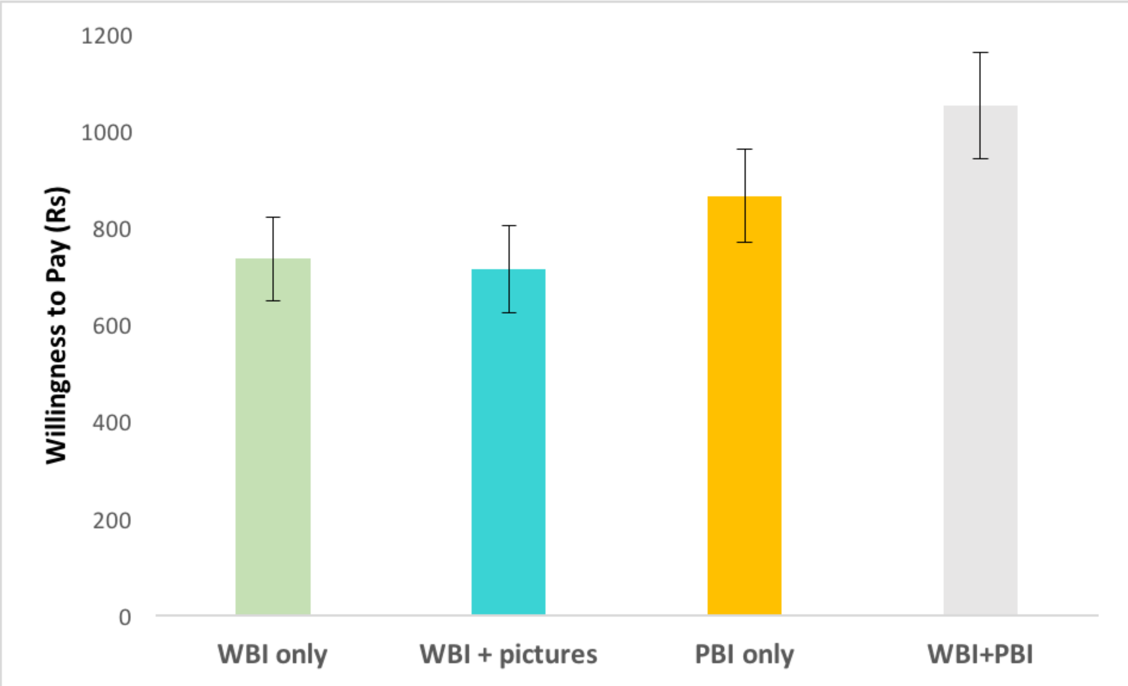
As a more standard, and perhaps more reliable measure for farmers' valuations, we elicited the maximum amount a subsample of farmers were willing pay for four different products. We did so through the Becker-DeGroot-Marschak auction mechanism, with a special product offer being hidden on a scratch card, as discussed earlier. By comparing WTP for four different products - WBI only, WBI + pictures, WBI + PBI, and PBI only - we can analyze several aspects of the demand for these products, including the valuation of WBI and PBI as stand-alone products, the valuation of add-on PBI or WBI coverage in WBI or PBI products, respectively, and the disvalue of having to take pictures.

Figure 4 presents the average willingness to pay across all farmers in our sample for each of the four products. First, we compare the WTP for the WBI + PBI product with that for the WBI only product, as a measure of how much farmers are willing to pay for extra PBI coverage. If the number of pictures sent in during the Rabi 2016/17 season was equal across the treatment and control group because farmers do not value additional PBI coverage in a WBI product, we would expect to see an equal willingness to pay for these two product types as well. Farmers were willing to pay on average Rs. 736 for the WBI only product (left bar) and Rs. 1,052 for the WBI + PBI product, indicating that farmers' valuation of PBI add-on coverage is a significant Rs. 316 ($p < 0.01$). In addition, the WTP for the PBI only product is a significant Rs. 129 higher than the WBI only product (Rs. 866).

Interestingly, the willingness to pay for the WBI + pictures product—which requires farmers to take pictures of their crops regularly throughout the Rabi season—was only Rs. 21 lower than the willingness to pay for the WBI only product, and this difference was not statistically significant. Contrary to our expectations, the perceived burden of having to take pictures of their crops on a regular basis does not seem to affect farmers' willingness to pay by a significant amount. Farmers were aware of the fact that the WBI +

pictures product would not come with new smartphones or free data plans. The finding that their WTP for this product is not significantly lower than the WTP for the WBI only product suggests that farmers are willing to take pictures in the absence of these incentives.

**Figure 4: Willingness to Pay for PBI versus WBI**




In sum, demand for PBI is stronger than for WBI, and having to take pictures does not appear to be a major barrier to enroll.

### 8.2 Outcome 2: Costs of WBI versus PBI

In our study, the PBI product was given to the farmers free of cost. However, in order for PBI to be sustainable, it is important to consider the incremental cost of premiums under real market conditions. Currently, the insurance premium of the *WBI only* product is Rs. 3,473, far above the average willingness to pay. We are currently looking into ways to reduce the cost of the WBI component in the product, for instance by taking out coverage for excess rainfall and instead covering this through the smartphone pictures, and crop models are suggesting that we can set the trigger for the temperature index at least one or two degrees Celsius higher, which reduces expected payouts and hence the insurance premium.

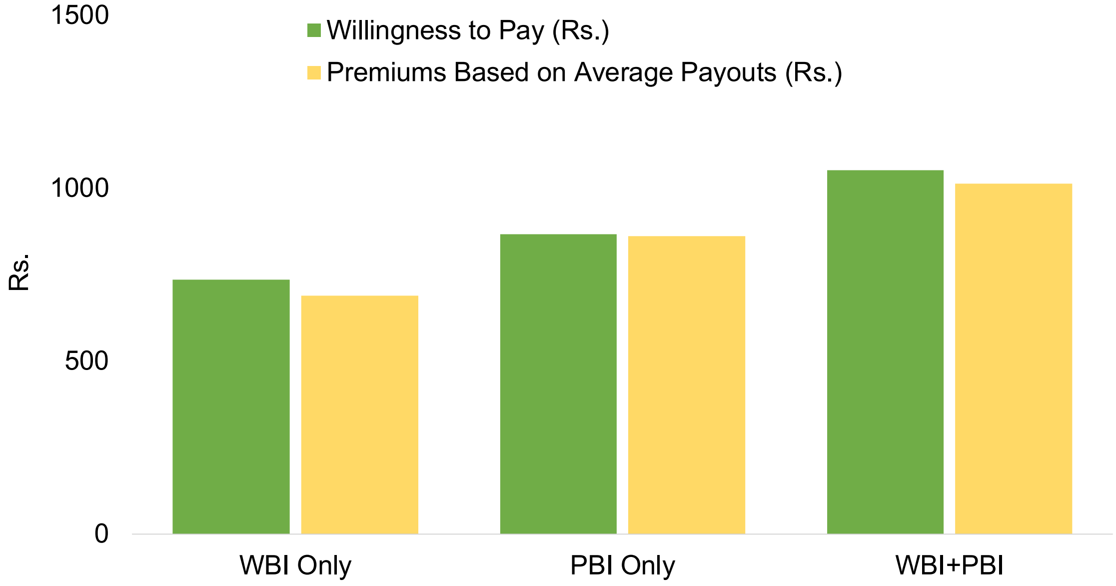
We also find that the increased willingness to pay for WBI + PBI was not sufficient to cover the insurance premium for the PBI add-on product, which was Rs. 660. It is important to note, however, that without historical data to price the PBI product, this Rs. 660 included an additional uncertainty premium. Further, wheat yield variability is relatively low in Haryana and Punjab, which was not taken into consideration in the pricing. Increased data availability could further reduce the premium mark-up. Thus, in our study area, Rs. 660 is most likely an upper bound of the amount by which the insurance premium would increase when adding PBI coverage to a WBI product.

In Figure 5, we therefore compare the willingness to pay for *WBI only*, *PBI only* and *WBI + PBI,* with an alternative, hypothetical premium calculated using average payouts per farmer during Rabi 2016-2017 season, plus a reasonable 30 percent loading factor. Insurance pricing is typically done based on the historical average payout, as a proxy for expected payouts, given the product parameters. This expected payout is multiplied by a loading factor to cover administrative and underwriting costs. In our formative evaluation, we were covering a small number of farmers relative to the number of weather stations for which HDFC needed to procure weather data; we were using weather stations for which there were no historical data; and the PBI approach was new to HDFC, meaning that there was a high uncertainty loading factor. As more historical data becomes available and the scale of the product increases, one would expect insurance companies to reduce loading factors and eventually converge to the 30% benchmark that is commonly referred to in the international insurance community. We find that farmers' average willingness to pay is slightly above these calculated insurance premiums for each of the three products, suggesting that the problem is not so much farmers' low willingness to pay, but high loading and uncertainty factors.

In future analyses, we will explore in more detail the validity of using a 30 percent loading factor in estimating insurance premiums in the presence of increased data availability. One thing to note in this regard is that although current loading factors in the Indian insurance market are higher than 30 percent, this is in part related to the lack of historical data, the reliance on intermediaries (which receive a commission of 15% of the insurance premium) instead of low-cost technology for enrollment (which would remove the need for intermediaries), and to the need for crop cutting experiments and validations of these yield measurements for claims settlement. In fact, during our study, loss assessments based on smartphone pictures by agronomists and other experts were about half the cost of the CCEs that we conducted (USD 5.35 per farmer vs USD 10.71 per farmer, respectively), and we would expect this cost to reduce further as we start automating image processing and claims settlement.

Having said that, in the near future, the willingness to pay for insurance—regardless of the product under consideration—falls short of the product costs, meaning that without subsidies, insurance is difficult to sell. We are hence considering offering PBI coverage by tapping into existing subsidized insurance schemes, such as the PMFBY and RWBCIS. The average WTP for the WBI product was 5.7 percent of the insured sum of Rs. 13,000. PBI add-on coverage increased the WTP to 8.3 percent of the insured sum. The WTP for picture-based insurance as a stand-alone product—without using weather indices—was 6.7 percent of the insured sum. After subsidies, PMFBY and RWBCIS premiums range from 1.5 to 5 percent of the insured sum. If these rates were applied to the products that we tested, the average farmer would be willing to pay the required premium rates, and at premiums equal to Rs. 600 or 4.6% of the insured sum, the results on willingness to pay suggest uptake of the WBI + PBI product for 78% of the target population. This implies a quite substantial take-up rate compared to other products.

**Figure 5: Expected Premiums and Willingness to Pay**




## 8.4 Balance, attrition and treatment fidelity

This subsection first investigates whether randomized assignment to treatment resulted in balanced baseline characteristics for farmers in treatment villages versus control villages. Table 3 presents summary statistics for farmers in the full sample (Columns 1 and 2), for the treatment group (Columns 3 and 4) and the control group (Columns 5 and 6). Columns 7 and 8 present the probability that baseline characteristics differ across the two samples, clustering standard errors used for inference at the village level. The majority of baseline characteristics is indeed balanced. with the exception of total area, use of zero tillage with Happy Seeder, and leaving crop residue untouched. These characteristics will be used as control variables in our analysis.

**Table 3: Balance Table Across Treatment Arms**

| | Full Sample | | WBI + pics | | WBI+PBI | | Diff. | *p*-value |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***Panel A: Farmer characteristics*** | | | | | | | | |
| Age of farmer | 39.14 | 11.77 | 39.48 | 12.00 | 38.81 | 11.85 | -0.621 | 0.5521 |
| Farmer is male | 0.999 | 0.037 | 1.000 | 0.000 | 0.997 | 0.053 | -0.003 | 0.1662 |
| Scheduled/other backward caste | 0.102 | 0.303 | 0.126 | 0.332 | 0.088 | 0.283 | -0.035 | 0.2623 |
| Has some tertiary education | 0.438 | 0.496 | 0.439 | 0.497 | 0.437 | 0.497 | -0.003 | 0.9119 |
| Farmer is married | 0.864 | 0.343 | 0.872 | 0.335 | 0.851 | 0.357 | -0.02 | 0.2769 |
| Farmer has a data plan | 0.686 | 0.464 | 0.687 | 0.465 | 0.668 | 0.472 | -0.021 | 0.4221 |
| Takes pictures often | 0.774 | 0.418 | 0.761 | 0.427 | 0.794 | 0.405 | 0.032 | 0.1881 |
| Household size at baseline | 6.240 | 2.583 | 6.222 | 2.626 | 6.220 | 2.526 | 0.007 | 0.9628 |
| Nr. Organizations | 0.780 | 0.790 | 0.806 | 0.769 | 0.786 | 0.816 | -0.021 | 0.6499 |
| ***Panel B: Farming characteristics*** | | | | | | | | |
| Nr. years of farming experience | 15.592 | 10.463 | 16.165 | 11.19 | 15.206 | 10.043 | -0.873 | 0.2970 |
| Received training in farming | 0.088 | 0.284 | 0.091 | 0.288 | 0.087 | 0.283 | -0.002 | 0.8969 |
| Number of plots | 2.36 | 0.666 | 2.356 | 0.624 | 2.355 | 0.704 | 0.003 | 0.9379 |
| Total area of plots (acres) | 8.845 | 3.981 | 9.15 | 3.990 | 8.49 | 3.938 | -0.674 | 0.0167** |
| % of land that the farmer owns | 89.336 | 24.582 | 89.136 | 25.55 | 89.087 | 24.306 | -0.259 | 0.8737 |
| % with rice in Kharif 15 | 0.856 | 0.322 | 0.862 | 0.329 | 0.848 | 0.323 | -0.016 | 0.4000 |
| % with wheat in Rabi 15/16 | 0.963 | 0.132 | 0.97 | 0.121 | 0.96 | 0.141 | -0.010 | 0.4194 |
| Yield Rabi 2015/16 (quintals/acre) | 19.593 | 2.104 | 19.773 | 2.169 | 19.495 | 2.073 | -0.280 | 0.1815 |
| Has burned crop residue | 0.769 | 0.422 | 0.752 | 0.432 | 0.774 | 0.419 | 0.023 | 0.4901 |
| Distance of plot to home (min) | 16.331 | 20.016 | 15.222 | 17.97 | 17.334 | 21.623 | 2.002 | 0.1115 |
| Distance of plot to WS (km) | 3.488 | 1.877 | 3.415 | 2.094 | 3.429 | 1.571 | 0.128 | 0.714 |
| ***Panel C: Financial access*** | | | | | | | | |
| Has crop insurance through KCC | 0.048 | 0.213 | 0.046 | 0.209 | 0.045 | 0.208 | 0.001 | 0.9604 |
| Borrowed money for Rabi 2015/16 | 0.837 | 0.37 | 0.846 | 0.361 | 0.837 | 0.37 | -0.012 | 0.5677 |

| | Full Sample | | WBI + pics | | WBI+PBI | | Diff. | *p*-value |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Has a bank account | 0.984 | 0.127 | 0.986 | 0.119 | 0.98 | 0.139 | -0.005 | 0.3615 |
| Could get a loan if needed | 0.746 | 0.436 | 0.744 | 0.437 | 0.743 | 0.438 | -0.004 | 0.8916 |
| | | | | | | | | |
| ***Panel D: Risk mitigation*** | | | | | | | | |
| Used laser land leveler | 0.707 | 0.455 | 0.721 | 0.449 | 0.678 | 0.468 | -0.044 | 0.1708 |
| Used zero till with Happy Seeder | 0.094 | 0.292 | 0.117 | 0.322 | 0.073 | 0.261 | -0.044 | 0.0404** |
| Left crop residue untouched | 0.088 | 0.284 | 0.108 | 0.311 | 0.071 | 0.257 | -0.037 | 0.0808* |
| Total N | 736 | | 366 | | 370 | | | |

*Notes:* Sample includes all respondents with a baseline interview. Column (8) presents p-values from a regression of the shown variable against a dummy variable equal to one if respondent is in the WBI+PBI treatment group, with weather station fixed effects, and standard errors clustered at the weather station level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also investigate to what extent attrition could be a confounding factor in the study findings. Table 4 shows the percentage of respondents that completed each stage in which attrition occured: enrolling in Wheatcam ( equal to one if the farmer took at least one picture), uploading smartphone pictures (equal to one if the farmer uploaded at least two pictures in 2017, and zero otherwise); crop cutting experiments (equal to one if the team was able to conduct a CCE on the farmer’s plot, and zero otherwise); and endline (equal to one if the farmer was interviewed at endline, and zero otherwise). Amongst the farmers who took pictures, about 80% qualified for a loss assessment (took more than 2 pictures in 2017). Amongst these farmers, almost 90% completed a CCE. In addition, attrition from the baseline survey to the endline survey was only around 6%.

**Table 4: Attrition Rates**

| | Full Sample | | WBI + pictures | | WBI + PBI | | | |
|---|---|---|---|---|---|---|---|---|
| | % Respondents (1) | N (2) | % Respondents (3) | SD (4) | % Respondents (5) | SD (6) | Diff (7) | p-value (8) |
| Enrolled in Wheatcam | 0.635 | 736 | 0.680 | 0.467 | 0.589 | 0.493 | -0.108 | 0.001*** |
| Took at least two pictures in 2017 | 0.511 | 736 | 0.549 | 0.498 | 0.478 | 0.5 | -0.084 | 0.013** |
| Took at least two pictures in 2017 conditional on Enrolling into Wheatcam | 0.805 | 467 | 0.807 | 0.395 | 0.812 | 0.392 | 0.009 | 0.697 |
| Completed Crop Cutting Experiment | 0.602 | 736 | 0.642 | 0.48 | 0.562 | 0.497 | -0.079 | 0.030** |
| Completed Crop Cutting Experiment Conditional on 2+ Pictures | 0.886 | 376 | 0.900 | 0.3 | 0.859 | 0.349 | -0.019 | 0.371 |
| Completed Endline Survey | 0.938 | 736 | 0.943 | 0.233 | 0.932 | 0.251 | -0.01 | 0.449 |
| Completed Endline Survey Conditional on 2+ Pictures | 0.984 | 376 | 0.980 | 0.14 | 0.989 | 0.106 | 0.01 | 0.174 |

Notes: This table presents the attrition rates from both are baseline sample, and conditional of taking 2+ pictures in 2017. Column (8) presents p-values from a regression of the shown variable against a dummy variable equal to one if respondent is in the WBI+PBI treatment group, with weather station fixed effects, and standard errors clustered at the weather station level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5, we test whether attrition is correlated with baseline characteristics, and whether attrition on observed characteristics is balanced between treatment and control groups. To this end, we estimate a probit model with as dependent variable an indicator for whether data are missing for an activity during which attrition occurred (equal to one if the data are missing, equal to zero otherwise) on various baseline characteristics. We present these estimates for each of the following stages at which attrition occurred: uploading smartphone pictures (indicator equal to one if the farmer uploaded at least one picture) in Columns (1)-(3); crop cutting experiments (indicator equal to one if no

CCE was completed) in Columns (4)-(8); and completing the endline survey (indicator equal to one if no endline survey was completed) in Columns (9)-(12). We report the estimated marginal effects and the probability that estimated coefficients differ between the treatment and control group.

Being in a scheduled caste, household size, and whether the farmer borrowed money in the previous year are correlated with taking at least one picture in the control group. However, these coefficients are not significantly different from coefficients estimated for the treatment group, except for household size. Joint significance tests for interaction effects between these covariates and a dummy variable indicating treatment status fail to reject the null hypothesis of no statistical differences (*p*=0.5068).

**Table 5: Differential Attrition for Unconditioned Samples**

| | **Does not have Wheatcam** | | | **No Crop Cutting Experiment** | | | **No Endline** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **(1)<br>PBI** | **(2)<br>WBI** | **(3)<br>p-value** | **(4)<br>PBI** | **(5)<br>WBI** | **(6)<br>p-value** | **(7)<br>PBI** | **(8)<br>WBI** | **(9)<br>p-value** |
| Age of Farmer | 0.00117 | -0.0014 | 0.719 | -0.0029 | -0.005** | 0.344 | 0.00538 | -0.00111 | 0.186 |
| | (0.005) | (0.004) | | (0.0049) | (0.0027) | | (0.0056) | (0.0042) | |
| | 0.215 | 0.171* | 0.904 | 0.160 | 0.201** | 0.437 | -0.959*** | 0.0806 | 0.883 |
| Scheduled/other Backward Caste | (0.133) | (0.104) | | (0.129) | (0.0961) | | (0.136) | (0.0797) | |
| | 0.0150 | -0.047 | 0.333 | 0.0469 | 0.00923 | 0.703 | -0.0002 | -0.0198 | 0.582 |
| Has some tertiary education | (0.053) | (0.043) | | (0.0498) | (0.052) | | (0.0475) | (0.0461) | |
| Farmer is married | 0.0557 | 0.0222 | 0.755 | 0.00116 | 0.0151 | 0.656 | -0.166** | 0.0140 | 0.067* |
| | (0.075) | (0.063) | | (0.0668) | (0.067) | | (0.0801) | (0.0433) | |
| | 0.0266 | 0.0862 | 0.477 | 0.0401 | 0.0129 | 0.945 | 0.0664 | 0.0543 | 0.705 |
| Farmer has a data plan | (0.071) | (0.063) | | (0.0753) | (0.0687) | | (0.0645) | (0.0554) | |
| | 0.0509 | -0.040 | 0.312 | 0.0940 | 0.0810 | 0.955 | -0.0851 | -0.144* | 0.473 |
| Farmer takes pictures often on phone | (0.068) | (0.061) | | (0.0784) | (0.0635) | | (0.0772) | (0.0787) | |
| | -0.0047 | 0.0008 | 0.507 | 0.00548 | 0.00274 | 0.918 | -0.00640 | -0.00204 | 0.486 |
| Nr. Years of farming experience | (0.006) | (0.005) | | (0.0060) | (0.0033) | | (0.0053) | (0.0047) | |
| | -0.0527 | -0.0583 | 0.924 | -0.149* | -0.0552 | 0.718 | - | -0.116 | - |
| Received formal training | (0.099) | (0.087) | | (0.0854) | (0.0511) | | | (0.0729) | |
| Household size | -0.0065 | 0.018** | 0.0279** | -0.0047 | 0.0101 | 0.452 | -0.0175* | 0.00995 | 0.018** |
| | (0.009) | (0.008) | | (0.0133) | (0.0089) | | (0.0104) | (0.0067) | |
| Nr. Organizations that farmer belongs | 0.0129 | -0.0041 | 0.73 | -0.0144 | 0.0386 | 0.268 | -0.00740 | 0.0702** | 0.0752 |

| | Does not have Wheatcam | | | No Crop Cutting Experiment | | | No Endline | | |
|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| | **PBI** | **WBI** | **p-value** | **PBI** | **WBI** | **p-value** | **PBI** | **WBI** | **p-value** |
| to | (0.034) | (0.034) | | (0.0362) | (0.0439) | | (0.0439) | (0.0339) | |
| Number of Plots | -0.0072 | -0.0226 | 0.786 | 0.00781 | -0.0192 | 0.332 | 0.0632 | 0.0303 | 0.937 |
| | (0.044) | (0.046) | | (0.0428) | (0.0438) | | (0.0476) | (0.0404) | |
| Total Area Owned | -1.3e-05 | -0.0032 | 0.701 | 0.00117 | 0.00154 | 0.659 | -0.00810 | -0.00626 | 0.806 |
| | (0.007) | (0.006) | | (0.0065) | (0.0059) | | (0.0082) | (0.0043) | |
| Self- Reported Wheat Yield Rabi | 0.0165 | 0.0049 | 0.599 | 0.0216* | 0.00292 | 0.83 | 0.00811 | 0.00614 | 0.94 |
| 2015/16 | (0.015) | (0.013) | | (0.0126) | (0.0157) | | (0.0152) | (0.0103) | |
| | -0.0857 | -0.0074 | 0.693 | -0.0052 | -0.005 | 0.697 | 0.0683 | - | - |
| Has crop insurance KCC | (0.136) | (0.126) | | (0.126) | (0.133) | | (0.105) | | |
| Borrowed Money for Ag Activities | -0.0941 | -0.20*** | 0.204 | -0.114 | -0.119* | 0.493 | 0.0388 | 0.00889 | 0.29 |
| 2015/16 | (0.077) | (0.058) | | (0.0713) | (0.0666) | | (0.0617) | (0.0434) | |
| Has Bank Account | -0.318 | -0.272 | 0.97 | -0.363* | -0.0259 | 0.428 | - | | |
| | (0.198) | (0.174) | | (0.194) | (0.163) | | | | |
| | 0.0203 | 0.0440 | 0.749 | 0.0373 | 0.0394 | 0.682 | -0.0840 | -0.0342 | 0.799 |
| Could Get a Loan if Needed | (0.057) | (0.065) | | (0.0535) | (0.0750) | | (0.0685) | (0.0624) | |
| | 0.0444 | 0.0452 | 0.941 | -0.0216 | -0.0771 | 0.794 | 0.0722 | -0.0706 | 0.174 |
| Used Laser Land Leveler | (0.061) | (0.059) | | (0.0797) | (0.0661) | | (0.0734) | (0.0673) | |
| | -0.0431 | -0.0935 | 0.651 | 0.0405 | 0.0893 | 0.551 | 0.0651 | 0.153*** | 0.633 |
| Used Zero Tillage with Happy Seeder | (0.074) | (0.105) | | (0.0906) | (0.0962) | | (0.0702) | (0.0575) | |
| Burned crop residue | 0.0469 | 0.0974 | 0.526 | 0.126 | 0.0379 | 0.975 | 0.0146 | 0.0424 | 0.768 |
| | (0.075) | (0.06) | | (0.0977) | (0.0755) | | (0.0674) | (0.0617) | |
| | -0.0591 | -0.0057 | 0.528 | -0.0583 | -0.129** | 0.443 | -0.0683 | -0.0269 | 0.545 |
| Uses weather forecasts | (0.053) | (0.052) | | (0.0542) | (0.0655) | | (0.0472) | (0.0445) | |

Note: This table reports the marginal effects estimated in a probit model for the likelihood of attrition. Dependent variables are dummy variables for whether the farmer is absent in the following samples: farmers with at least one uploaded picture in Columns (1)-(3); those with a crop cutting experiment in Columns (4)-(6); and those with an endline survey in Columns (7)-(9). Standard errors are clustered at the village level. Columns (3), (6), and (9) present *p*-values from interacting the stated independent variable with a dummy variable indicating "PBI" in a model estimated with observations from both the WBI and the PBI sample. *** p<0.01, ** p<0.05, * p<0.1

Regarding participating in the crop cutting experiments in Columns (4)-(6), age and belonging to a backwards caste are both correlated with attrition in the control group. However, as before, there is no statistically significant difference between coefficients estimated for the control group and the treatment group, with joint significance tests indicating that selection on observed characteristics follows a similar pattern in the two treatment arms (p=0.899).

Columns (7)-(9) do suggest that attrition patterns are significantly different between the control group and the treatment group in two ways: married farmers and larger households are less likely to miss the endline survey in the treatment group, whereas this is not the case in the control group. Reweighing observations based on the probability of dropping out does not affect our results, most likely because attrition between baseline and endline is limited to 6%.

Finally, we perform a manipulation check for whether farmers in the two different treatment arms correctly understood that they would be covered for excess rainfall and extreme heat only (in the WBI group), or also for visible damage in their pictures (in the WBI + PBI group). Table 7 shows that most farmers understood what the insurance product covered. More than 90% of farmers in the PBI group (Column 5) understood that the insurance products covered them for visible damage, and the coverage for visible damage was more salient to them than the coverage for excess rainfall or extreme heat.

Interestingly, however, more than half of the WBI control group believed that the WBI product also covered visible damage, indicating some misunderstanding of the WBI only product. This is likely due to the conditioning of weather index-based insurance coverage on regularly sending in pictures also in the WBI group. This could potentially introduce a downwards bias in the moral hazard estimates, because farmers in the control group perceiving to have PBI coverage may have had the same disincentives to invest in good management practices as farmers in the treatment group. Although we report intent to treat estimates in our main estimates, we instrumented, as a robustness check, the (endogenous) self-perceived coverage by a farmer's (exogenous) assignment to treatment, and found that our main findings and conclusions are robust to this specification.

**Table 6: Understanding of Coverage**

| | Full sample | | WBI + pics | | WBI + PBI | | | |
|---|---|---|---|---|---|---|---|---|
| *Does insurance product cover…* | Mean | SD | Mean | SD | Mean | SD | Diff | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Excess rainfall? | 0.892 | 0.311 | 0.901 | 0.3 | 0.883 | 0.322 | -0.015 | 0.5527 |
| Extreme heat? | 0.830 | 0.376 | 0.829 | 0.377 | 0.831 | 0.376 | 0.004 | 0.9072 |
| Visible damage in pictures? | 0.745 | 0.436 | 0.565 | 0.497 | 0.923 | 0.497 | 0.361 | 0.0000*** |

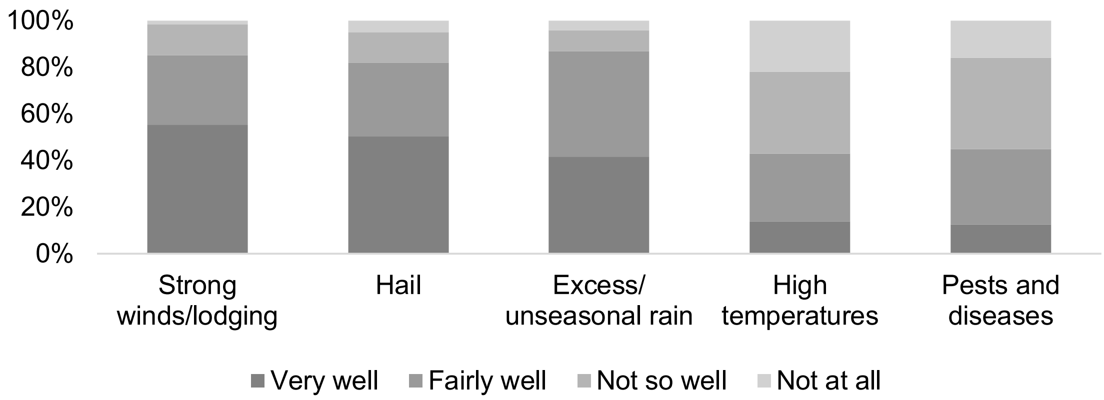
Notes: This table presents summary statistics on the extent to which farmers understand the insurance products assigned to them. Column (8) presents p-values from a regression of the shown variable against a dummy variable equal to one if respondent is in the WBI+PBI treatment group, with weather station fixed effects, and standard errors clustered at the weather station level. * p < 0.10, ** p < 0.05, *** p < 0.01.

## 8.5 Impact pathways

### *8.5.1 Assumption (1): Crop Damage can be Estimated from Images*

Our first assumption that leads farmers to value PBI over WBI is that damage can be captured through a time-series of images, and that the damage correlates well with yields. Farmers' perceptions already suggest that this is the case. Figure 6 shows that 80% of farmers believe that damages caused by lodging, hail, and excess rainfall can be "very well" or "fairly well" captured from direct visual inspection of a time-series of pictures.

**Figure 6: Farmers' Perceptions about the Visibility of Different Hazards in Pictures**




The results of the expert loss assessments show that the pictures can indeed pick up damage that is visible. Figure 7 shows a box plot of these assessments, ordered by the median assessment within a site. The level of agreement between experts is quite high for low levels of damage (under 20 percent), except for sites where the median damage is zero, which shows a number of outliers.  Even for sites with more severe damage (over 20 percent), most experts agree over the approximate region in which the damage occurs.

**Figure 7: Expert assessments for same site by median expert assessment for that site**

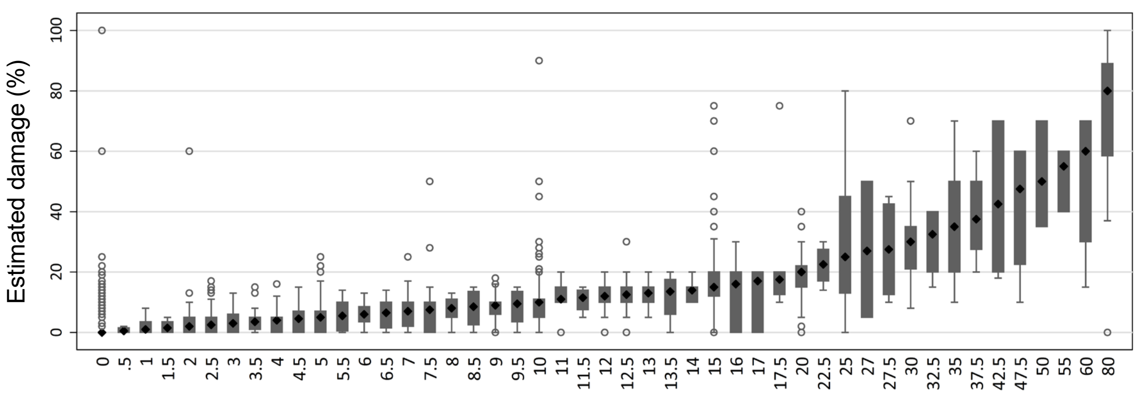



Table 7 Panel A shows the median damage from the loss assessments broken down into categories. In Panel B, we aggregate farmers with more than 20% damage and find that nearly 10% of farmers experienced a loss above 20%, triggering a payout. Given that in the study region, production risk in wheat is relatively low compared with other crops, this

is a realistic percentage of claims being realized. By contrast, WBI triggered payouts for a significantly higher 22.2% of farmers, which is an implausibly high number given that no widespread damage due to excess rainfall or extreme heat was reported in the Rabi 2015/2016 season. Moreover, if payouts were triggered, the amount for PBI was higher on average than the amount for WBI (Panel C). This could be indicative of PBI identifying farmers with substantial damage, resulting in higher payouts, whereas WBI payouts may have been triggered too easily, for farmers not experiencing damage.

**Table 7: Loss Assessments and Insurance Payouts**

| | Mean (1) | SD (2) | Median (3) | Min (4) | Max (5) | N (6) |
|---|---|---|---|---|---|---|
| *Panel A: Loss assessment categories* | | | | | | |
| Not damaged: 0 – 20% | 0.907 | 0.280 | 1 | 0 | 1 | 376 |
| Slightly damaged: 20 – 50% | 0.067 | 0.238 | 0 | 0 | 1 | 376 |
| Severely damaged: 50 – 75% | 0.023 | 0.151 | 0 | 0 | 1 | 376 |
| Fully damaged: 75 – 100% | 0.002 | 0.048 | 0 | 0 | 1 | 376 |
| *Panel B: Triggering of indices* | | | | | | |
| WBI index triggered | 0.222 | 0.416 | 0 | 0 | 1 | 376 |
| PBI index triggered | 0.093 | 0.290 | 0 | 0 | 1 | 376 |
| *Panel C: Payout if index triggered* | | | | | | |
| WBI payout | 2429 | 646.7 | 2128 | 1671 | 3751 | 83 |
| PBI payout | 5163 | 2195 | 3900 | 3900 | 13000 | 37 |

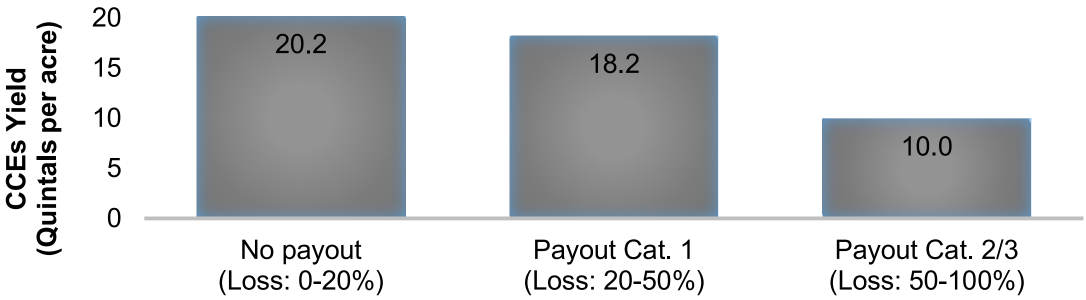
Notes: Panel A breaks the median loss assessments into categories. The mean represents the proportion of farmers who qualified for a loss assessment that fell into each respective category. Panel B shows how many farmers received a payout (index was triggered or had a loss over 20% from the pictures). Amongst those who received a payout, Panel C shows the average payout conditional upon the index triggering. Additional payouts from PBI over WBI is the average additional payout from PBI conditional on either of them triggering.

To corroborate this claim, we assess how well insurance payouts based on damage visible in the smartphone pictures perform compared with insurance payouts based on weather indices. Figure 8 compares yields measured objectively through crop cutting exercises amongst those who received a WBI payout, and did not receive a WBI payout (panel A); and those who received a PBI claim, and did not receive a PBI claim (panel B). Yields do not differ in a statistically significant way for those with and without a WBI claim; however, yields are lower on average for those who received a PBI payout, compared to those that did not, and the difference is most pronounced for cases where damage was assessed to be more severe. This indicates that the visible damage from the PBI can capture more objective losses than WBI. In other words, basis risk is reduced.

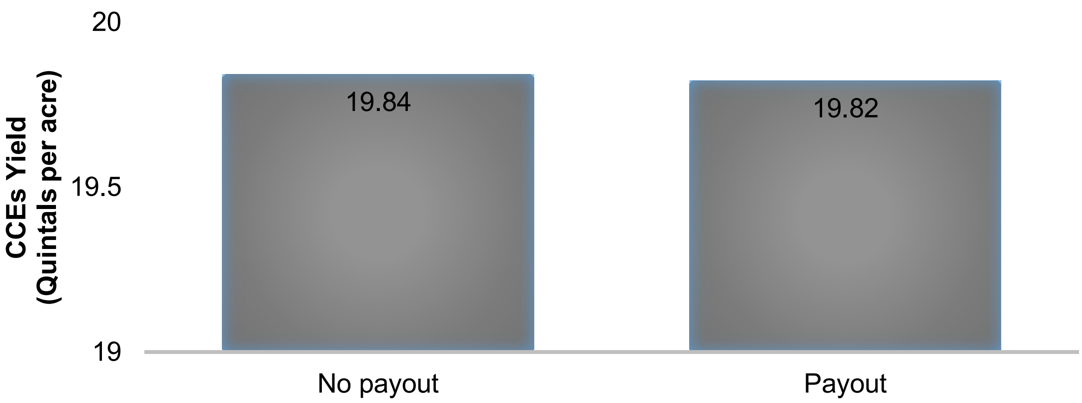
In sum, we find that farmers perceive most hazard to be visible from smartphone pictures, and experts agreed to a large extent on the degree of damage visible in a site based on the pictures they reviewed. Although the PBI product triggered for fewer farmers than the WBI component, the average payouts triggered by PBI were higher and PBI payouts were better correlated with yields than the WBI payouts. This indicates that the PBI product helped reduce basis risk substantially, offering an explanation for why farmers are willing to pay more for PBI products than for products that only include WBI coverage.

**Figure 8: Correlation between yields and payouts**

**A. PBI payouts**




**B. WBI payouts**




***8.5.2 Assumption (2) Ownership, trust, and understanding is low.***

The second assumption in our TOC that would lead farmers to have a higher WTP for PBI compared to WBI, is that ownership, trust, and understanding in conventional WBI products is low. The intervention will be relevant in the study context if farmers indicate they do not trust other crop insurance products and important product components such as whether the product covers losses, and whether it pays out when they experience losses. The take-up of other weather-based index insurance products is very low in our sample, at only about 5%, meaning that a very small proportion of farmers has previous experience with (and payouts from) such insurance products. During focus group discussions, farmers also raised concerns around other insurance approaches, including distrust in satellite imagery and poor correlation between weather and crop yields in their plot, whereas they were enthusiastic about the idea of basing insurance on smartphone pictures. They believed that it could cover risks such as lodging, and pests and diseases.

During focus group discussions, farmers indicated distrust in the current crop insurance schemes. For instance, crop insurance is compulsory under the Kisan Credit Card (KCC) scheme in Haryana, but farmers participating in the focus groups were often not aware of this coverage. Moreover, those who were aware stated that they would never receive insurance payouts, because the payments would go to individuals in the village who had strong social ties with the local community leaders. Some farmers even reported that they had asked the bank agents to take out the deduction for insurance premiums, reflecting poor ownership. We also find evidence of poor awareness in our quantitative data: only 19% of baseline farmers who took out KCC loans in Haryana reported to be covered despite compulsory enrolment.

We find low levels of trust in crop insurance in our sample also at endline. Table 8 shows the level of trust in various aspects of insurance, reported by the endline sample. In Column (1), trust in the accuracy in weather station measurements, and how it reflects conditions on the plots, are quite low, with around 15%-21% of respondents reporting "a lot of trust" in these components. Trust in insurance companies is slightly higher, with 32.1% and 30.9% of farmers reporting "a lot of trust" in insurance companies to pay if they are supposed to, and to make payouts by the end of May, respectively.

**Table 8: Trust for Insurance Products is Low**

| | Sample | | WBI + pics | | WBI + PBI | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | N | Mean | N | Diff | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Weather station (WS) is accurate | 0.212 | 0.409 | 0.214 | 322 | 0.209 | 325 | -0.005 | 0.8473 |
| Rainfall in WS reflects rainfall on your plot | 0.168 | 0.375 | 0.189 | 322 | 0.148 | 325 | -0.04 | 0.0829* |
| WS temperatures reflect temperature on plot | 0.176 | 0.381 | 0.196 | 322 | 0.157 | 325 | -0.038 | 0.159 |
| Insurance company will pay if supposed to | 0.321 | 0.467 | 0.289 | 322 | 0.354 | 325 | 0.07 | 0.0294** |
| Insurance company will pay out at the end of May | 0.309 | 0.462 | 0.339 | 322 | 0.280 | 325 | -0.052 | 0.0877* |

Note: This table shows the proportion of farmers reporting *"some trust" or "a lot of trust"* in the respective insurance components. Column (8) presents *p*-values from a regression of the shown variable against a dummy variable equal to one if respondent is in the WBI+PBI treatment group, with weather station fixed effects, and standard errors clustered at the weather station level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

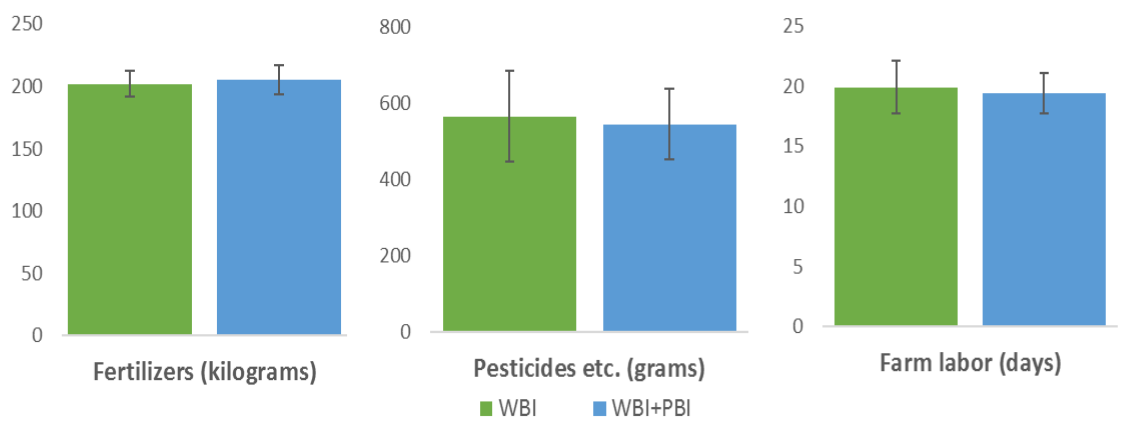
Columns (7) and (8) compare the difference in levels of trust between control (Columns 3 and 4), and treatment (Columns 5 and 6). Interestingly, farmers in the PBI group report higher trust in the insurance company paying out if they are supposed to, compared with those in the WBI group. This may be due to the idea that pictures can be used as proof of losses for the insurance companies. At the same time, a number of trust indicators are lower for the PBI group, including trust in weather stations being able to capture rainfall on the farmers' plots, and insurance companies paying out at the end of May.

In sum, we find evidence of low product ownership, trust and awareness of existing insurance products and of the WBI product that we offered to farmers in the control group. Although PBI coverage increased the probability of farmers reporting "a lot of trust” in the insurance company to pay if it is supposed to, the difference was not as substantial (28.9% to 35.4%) as the significant reduction in basis risk that we observed. We conclude that in this formative evaluation, the higher willingness to pay for PBI was more likely caused by a reduction in basis risk than by an improvement in trust, understanding and awareness.

***8.5.2 Assumption (3) PBI does not induce moral hazard and adverse selection***

The third assumption that we are testing is that picture-based insurance coverage does not create disincentives for farmers to mitigate risk and manage their crops well, in other words, that PBI does not induce moral hazard, which would increase the costs of providing insurance coverage. Figure 9 illustrates the difference in input use between farmers who were randomly assigned to receive the WBI product (control group), and those assigned to receive the WBI + PBI product (treatment group). Figure 4 shows that the usage of fertilizers (left chart), pesticides, fungicides, and herbicides (middle chart), and farm labor (right chart) are statistically indistinguishable between the two types of farmers. Thus, at the most direct level of input usage, we find no evidence of moral hazard.

**Figure 9: PBI Coverage does not Affect the Quantity of Inputs Used**




In Table 9, we replicate this finding for input usage at a more disaggregated level (see Appendix 2 for summary statistics of these variables). We estimate the effect of being randomly assigned to receive WBI+PBI coverage on the use of different types of fertilizer (in kilograms), the use of pesticides versus herbicides (in grams), and different types of labour (in days). For urea, we observe a negative but statistically insignificant coefficient, meaning we cannot reject the null hypothesis that there is moral hazard. For DAP, and potash, the coefficients are positive, providing further evidence that PBI did not induce moral hazard. For pesticides, herbicides, and hired male and female labour, the estimates are again negative, but statistically insignificant. Own labor use is higher in the treatment group, but not again not significantly, lending to the conclusion that in terms of input usage, we find no evidence of moral hazard.

**Table 9: PBI does not Cause any Difference in Inputs**

| | (1) Urea (Kgs) | (2) DAP (Kgs) | (3) Potash (Kgs) | (4) Pesticides | (5) Herbicides | (6) Hired Male Labour (Days) | (7) Hired Female Labour (Days) | (8) Own Labour (Days) |
|---|---|---|---|---|---|---|---|---|
| PBI Villages | -0.510 | 0.725 | 0.594 | -6.939 | -33.60 | -0.146 | -0.0161 | 6.864 |
| | (1.010) | (0.930) | (0.483) | (11.86) | (25.79) | (0.274) | (0.0209) | (5.425) |
| Constant | 53.03*** | 59.53*** | 1.636** | 142.3*** | 309.0*** | 3.108*** | 0.0769* | 29.55* |
| | (1.960) | (1.539) | (0.777) | (17.78) | (28.46) | (0.425) | (0.0454) | (17.44) |
| Observations | 688 | 688 | 688 | 688 | 688 | 688 | 688 | 688 |
| Mean of Dep. Variable in Control | 50.89 | 59.62 | 1.725 | 159.2 | 311.6 | 4.832 | 0.0290 | 13.29 |
| R-squared | 0.113 | 0.355 | 0.09 | 0.133 | 0.155 | 0.100 | 0.041 | 0.035 |

Notes: The sample includes farmers who completed a baseline and endline survey. The treatment variable in this specification gives us the Intent-to-Treat estimate of whether farmers assigned to WBI+PBI villages changed the quantity of inputs used on their Wheatcam Plot. All inputs variables are normalized to per acre terms. Standard Errors are clustered at the village level. * p < 0.10, ** p < 0.05, *** p < 0.01.

In assessing whether there is moral hazard, we also estimate the effects of PBI coverage on overall yields and loss assessments. Input usage was self-reported by farmers, and PBI farmers may have overstated their input use. A more objective for moral hazard is whether PBI coverage corresponds to lower yields, or increased estimates of damage. Figure 10 summarizes yields measured through crop cutting experiments as well as the expert assessments of damage due and not due to mismanagement based on what they could observe in the smartphone pictures. The differences between the WBI group and the WBI + PBI treatment group are statistically indistinguishable for all three measures. This provides further evidence of PBI not inducing moral hazard. In fact, during focus groups at the end of the season, farmers reported that having to take pictures *improved* management practices, as they monitored their crops more closely.

In Table 10, we replicate these findings while controlling for variables imbalanced at baseline, and weather station fixed effects, through OLS regressions of yields and damages on a dummy variable indicating farmers were randomly assigned to the PBI treatment. In Column (1), we find no significant negative effect of PBI on yields measured through crop cutting experiments, while PBI does not significantly increase damage estimated during loss assessment in Columns (2)-(4). Although effect sizes are in a direction that would be consistent with moral hazard, the estimates are not significantly different from zero, and the study was powered sufficiently to identify meaningful effect sizes of a magnitude whereby moral hazard would become a problem to product sustainability.

**Figure 10: PBI Coverage does not Affect Yields or Assessed Damage**

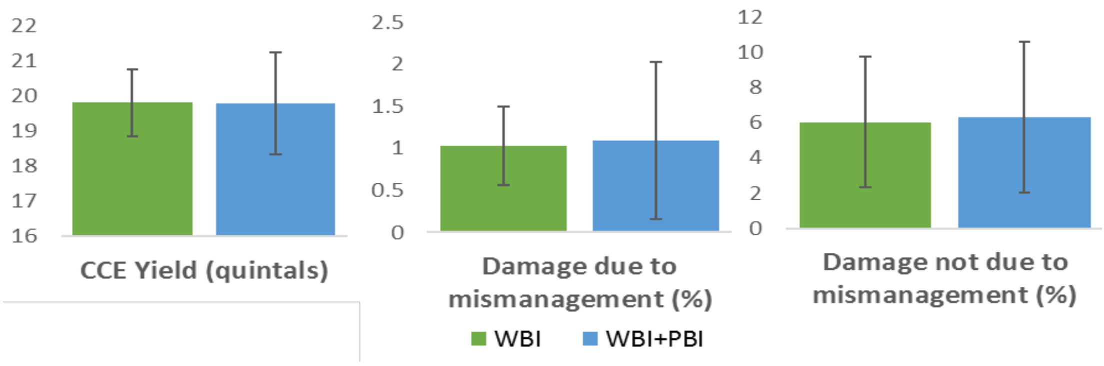



**Table 10: PBI does not Cause Any Difference in Yields**

| | (1) Crop Cutting Yields | (2) Median Damage Due to Mismanagement | (3) Median Damage Not Due to Mismanagement | (4) Median Total Damage |
|---|---|---|---|---|
| PBI Treatment | -0.383 | 0.162 | 0.683 | 0.882 |
| | (0.585) | (0.512) | (2.069) | (2.131) |
| Constant | 22.45*** | 0.0719 | 10.56*** | 11.04*** |
| | (0.304) | (0.200) | (1.629) | (1.425) |
| Observations | 437 | 413 | 413 | 413 |
| Mean of Dep. Variable in Control | 19.79 | 1.061 | 6.157 | 7.740 |
| R-squared | 0.288 | 0.076 | 0.328 | 0.273 |

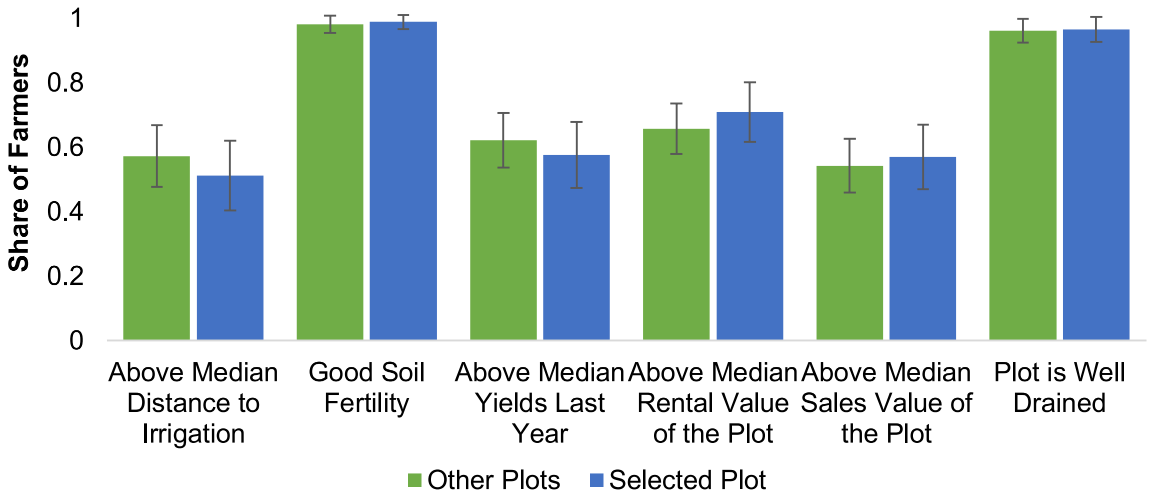
Notes: Standard errors are clustered at the village level. * p < 0.10, ** p < 0.05, *** p < 0.01.

An additional concern for the sustainability of PBI is the presence of adverse selection. If insurance is only purchased by farmers who are most at risk (who value it the most, since they expect the highest payouts), and for their most vulnerable plots, then insurance premiums would rise, causing farmers with lower risk exposure (and hence expecting lower insurance payouts) to drop out of insurance. This would further increase premiums, crowding out even more farmers and plots at lower risk, creating a feedback loop that could make the product unsustainable.

To test whether adverse selection was present amongst our sample, we analyzed—using the willingness to pay study—whether farmers selectively enrolled high-risk plots into PBI coverage. We study two aspects of adverse selection: at the farmer level and at the plot level. For the former, we test whether farmers with worse yields and farmers for whom experts detected damage in the crop pictures (arguably the riskier farmers) are willing to pay relatively more for PBI insurance coverage, but find no evidence of adverse selection at the farmer level (not reported here).

For the latter aspect, given that farmers had to select one plot to be insured during the willingness to pay study, we test for selection of plots with worse (i.e. riskier) characteristics. Specifically, we tested whether the plots that farmers choose to enroll in insurance are of lower quality, or of higher risk, than the plots that they choose not to enroll in insurance. To that end, Figure 11 shows comparisons of various quality indicators between the plot that the farmer selected to enroll in insurance and the other plots that the farmer opted not to enroll. Across a number of plot characteristics- such as how far the plot is from an irrigation source and from the home, soil type, drainage, area, and sales and rental value - we find no quality differences between those plots selected and those not selected for PBI coverage. Thus, PBI did not induce adverse selection.

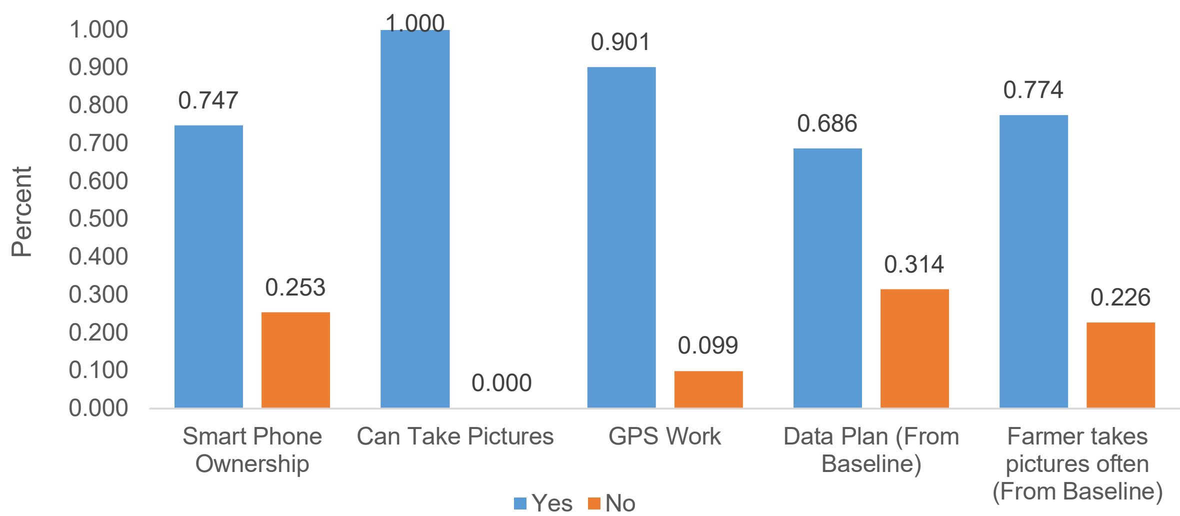
**Figure 11: No Evidence of Selective Enrolment**




### *8.5.3 Assumption 4. Farmers have a smartphone*

The final assumption is that costs of PBI remain low because the product leverages farmers' existing smartphone ownership. During the village census, we verified this assumption by asking farmers whether they owned a smartphone. We found that, out of the 1650 farmers interviewed, 74.7% owned a smart phone (Figure 12). In addition, conditional on having a smartphone, all farmers indicated that their phone had a working camera to take pictures and 90.1% of smartphones had a working GPS. At baseline, 68.6% of farmers had a data plan, and 77.4% took pictures often with his phone. This implies that smartphone ownership and usage is high, and that it is possible to leverage this existing technology in the provision of affordable insurance coverage.

**Figure 12: Smart Phone Ownership and Use**



# 9. Implications of study findings

## 9.1 Implications for the intervention

This study was the first to evaluate the feasibility of picture-based loss assessment, and study key outcomes determining product sustainability. We conjectured that compared with weather index-based insurance, a product relying on picture-based loss verification would increase the willingness to pay for insurance coverage, due to improved engagement with farmers and minimized basis risk. We further hypothesized that the costs of providing such insurance products remains low compared with the costs associated with standard indemnity yield-based insurance products, given that loss verification costs reduce substantially and moral hazard can be limited by using the pictures to monitor management practices prior to the occurrence of damage.

To test this theory of change, in June 2015, we sampled 750 smallholder wheat producers from 50 villages in six districts in Haryana and Punjab for a baseline survey. Of them, 592 agreed to participate in a study requiring them to regularly upload pictures of their wheat throughout the upcoming Rabi (winter) season using a smartphone app. In return for their participation, they received insurance coverage for one acre of wheat. Farmers were randomly assigned to receive only weather index-based insurance coverage(WBI), or to receive additional picture-based insurance (PBI) coverage for damage visible in uploaded images. Independent agronomic experts inspected uploaded series of smartphone pictures for visible damage, and in March 2017, just prior to harvest, we validated these loss assessments by measuring yields through crop cutting exercises. We established that PBI reduces basis risk and that PBI coverage did not reduce objectively measured yields, lower self-reported input use, or result in more visible damage, indicating that moral hazard remained limited. Finally, in July 2017, we measured willingness to pay for PBI versus WBI among 100 farmers and found that PBI increases uptake. Findings were compiled in a workshop in September of 2017 with key stakeholders to discuss implications of our findings, and the challenges moving forward.

Our first finding is that picture-based loss assessment is feasible from a demand-side perspective. Farmers are able, and willing, to take high-quality time-series of their crop from their smart-phones. We find that loss assessments for the same farmer correlate across experts, indicating that smartphone pictures have visible characteristics that indicative of damage, and farmers themselves perceive major sources of damage to be visible in smartphone pictures. We also find that picture-based loss assessment helped reduce the basis risk underlying our WBI product, offering an explanation for why farmers are willing to pay more for PBI coverage than for WBI. We find less evidence for the tangible, participatory nature of PBI driving the increase in demand.

Our second finding is that although the WTP for the combined WBI + PBI product is higher than it is for WBI only, the WTP is below market premiums for both products. For the PBI approach to be sustainable in the absence of premium subsidies, the market premiums would have to fall. As increased data availability would allow for a reduction in insurance loading factors and uncertainty premiums, it is reasonable to expect a decline in market premiums in future seasons. Indeed, for our study, loss assessments were already only half the cost of crop cutting experiments to measure area-yields (USD 5.35 per farmer vs USD 10.71 per farmer respectively). This cost is expected to reduce even more as increased data availability enables the development of indices and algorithms that automate image processing and loss detection. In addition, costs remain within bounds because–at least in this first study year—moral hazard did not occur, nor did we find evidence of adverse selection. Although it is important to test for dynamics over time, the present study suggests that the implemented repeat photography protocols help prevent distortion due to such information asymmetry problems.

The formative evaluation also yielded a few lessons related to assumptions and bottlenecks along the causal chain that we had initially not considered. First, we learnt that wheat—which we focused on due to synergies with an initial pilot project on climate-smart agriculture and due to the large number of farmers growing this crop—is perceived to be less risky than other crops. Expanding PBI coverage for more risky cash crops such as cotton or horticultural crops could have stronger impacts on agricultural investments, production and rural livelihoods, especially for horticultural crops, which are not covered in the PMFBY through village-level crop cutting experiments for loss assessment. Existing agricultural policies have led farmers to grow only one or two crops per season. Specialization into a rice-wheat cropping system puts extreme pressure on the ecosystem. Insurance for less common crops could help improve production diversity and thereby reduce water usage. In addition, by promoting production of cash crops, expanding insurance coverage to these cash crops could help improve agricultural incomes, and—in the case of horticultural cash crops—the increased diversity in production could result in improved dietary diversity within the household.

A second lesson learnt is that farmers' willingness to pay for a base level of insurance coverage, in our case weather index-based coverage, is low and bundling PBI with these types of products (resulting in a WBI + PBI product) would harm demand. Farmers' willingness to pay for the WBI component is so far below the cost of the WBI component that they would never take up the bundled product in large numbers. Hence, it would be ideal to bundle PBI with existing subsidized insurance schemes, which is why we are proposing to offer PBI as an add-on to the subsidized PMFBY schemes in Haryana, and—to assess external validity in an area with lower smartphone ownership and higher production risk—in Madhya Pradesh. This would also increase the scope for policymakers to adopt our findings in their ongoing operations; for instance, we have had conversations with the Haryana Department of Agriculture about the use of digital repeat photography and other technologies in reducing the number of crop cutting experiments required to implement the PFMBY, and expanding PMFBY coverage to new crops presently not included in the scheme.

In order to analyse whether PBI can reduce basis risk in the context of an area-yield index (AYI), we used our CCE and loss assessment data to simulate the proportion of farmers who would have received payouts under different types of products: AYI only (triggering when average yields measured for a random sample of farmers in a given area drop more than 20% below normal yields); PBI only (triggering when visible damage is either more than 20%, in case of a 'lenient policy', or 50%, in case of a 'strict policy', as assessed by subject matter experts); and a product that combines AYI and PBI. Table 11 presents average proportions of farmers receiving payouts and standard deviations from 10,000 simulations, whereby depending on the product type, each simulation randomly selects four farmers within a cluster of two nearby villages (weather station level) or a cluster of all villages within a district to determine the area-yield index for that cluster.

We include all farmers in Columns (1)-(2) as a proxy for average payouts. In Panel A, the area-yield index product would have triggered for on average 7.9 percent of farmers if yields were measured for a cluster of nearby villages (weather station level), and for 6.9 percent of farmers if measured at the district level. To also assess the degree of basis risk, Columns (3)-(8) distinguish between farmers with different levels of actual damage as measured through CCEs.[1] Although costlier and logistically more cumbersome, measuring yields for a cluster of nearby villages minimizes basis risk compared to measuring yields at the district level due to spatial correlation in yields. At the weather station level, the area-yield index identifies about half of all farmers with severe damage (50% or more), and about one fifth of all farmers with moderate damage (20-50%), which is twice the proportion identified through the district-level index.

Table 11 Panel B shows that PBI has both an advantage and a disadvantage compared with the AYI product used in the simulations. On the one hand, without triggering significantly more often on average, the lenient PBI policy triggers significantly more often than AYI for farmers with severe damage; and the stricter PBI policy triggers at least as often as AYI, but at significantly lower cost, as it rarely triggers for other farmers. On the other hand, while outperforming AYI in identifying farmers with severe damage, PBI does not help distinguish farmers with moderate damage from farmers with less or zero damage.

In Panel C, combining the lenient PBI policy with AYI therefore reduces downside basis risk compared with AYI, but also increases the proportion of farmers that receive payouts while not experiencing damage, leading to upside basis risk and higher costs of the insurance policy. However, in identifying farmers with severe damage, the district-level product now performs as well as the product measuring yields at the weather station level, and although not statistically significant, more farmers with moderate damage would receive payouts under the combined product than under the AYI only, even when yields are measured at the level of the weather station. In other words, PBI reduces downside basis risk at low cost, and can potentially help realize cost savings by reducing the number of CCEs required for loss indemnification in the AYI component.

Finally, the stricter policy in Panel D increases the overall proportion of farmers receiving payouts only slightly compared to the AYI products in Panel A, maintaining the weather station level AYI-PBI combination as a viable option. The product would have made payouts to 73.4 percent of farmers with severe damage, to 20.2 percent of farmers with moderate damage, and to only 5.2 percent of farmers with limited or no damage. Combined, these findings indicate that using pictures for loss assessment in combination with AYI can substantially reduce the downside basis risk that we observe in the simulations that help evaluate the AYI products, without significant increases in costs. These findings will be useful in further stakeholder engagement on introducing the PBI product into AYI schemes, for instance the PMFBY.

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[1] We avoid mechanical correlations with the level of damage in the CCEs for an individual farmer and the area-yield indices by omitting from a given simulation the farmers who were randomly selected for the area-yield index construction in that simulation. Given that the state governments normally select at most four farmers in villages with more than 100 farmers, whereas we have fewer farmers per village, we believe the results are more accurate when avoiding this mechanical correlation.

**Table 11: Simulations of area-yield index and picture-based insurance performance**

| | Probability of receiving payout | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | All farmers | | Has >=50% loss | | Has 20-50% loss | | Has < 20% loss | |
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **A. Area-yield index (AYI)** | | | | | | | | |
| Weather station level | 0.079 | 0.034 | 0.510 | 0.298 | 0.202 | 0.080 | 0.050 | 0.025 |
| District level | 0.069 | 0.106 | 0.247 | 0.409 | 0.097 | 0.149 | 0.059 | 0.090 |
| **B. Picture-based insurance (PBI)** | | | | | | | | |
| - Lenient policy (pay if >= 20% loss) | 0.097 | 0.009 | 0.750 | 0.079 | 0.073 | 0.027 | 0.071 | 0.009 |
| - Strict policy (pay if >= 50% loss) | 0.029 | 0.005 | 0.599 | 0.087 | 0.000 | 0.000 | 0.007 | 0.003 |
| **C. AYI + PBI: Lenient policy (>= 20%)** | | | | | | | | |
| Weather station level | 0.150 | 0.021 | 0.794 | 0.080 | 0.255 | 0.067 | 0.112 | 0.023 |
| District level | 0.151 | 0.083 | 0.771 | 0.094 | 0.150 | 0.137 | 0.122 | 0.079 |
| **D. AYI + PBI: Strict policy (>= 50%)** | | | | | | | | |
| Weather station level | 0.091 | 0.025 | 0.734 | 0.106 | 0.202 | 0.080 | 0.052 | 0.023 |
| District level | 0.091 | 0.094 | 0.666 | 0.157 | 0.097 | 0.149 | 0.064 | 0.087 |
| Number of observations in total* | 357 | | 14 | | 33 | | 310 | |
| Number of weather stations | 25 | | 5 | | 17 | | 25 | |
| Number of districts | 6 | | 2 | | 6 | | 6 | |

Notes: Mean and standard deviation based on a Monte Carlo simulation with 10,000 replications and 4 CCEs per geographical unit (weather station level or district level). We are not simulating area-yield indices at the village level due to a limited number of observations in villages. *Observations that are randomly selected for inclusion in the CCEs in a simulation are dropped from the payout analyses for that simulation in order to avoid mechanical correlations between the CCE yields and insurance payouts, which we would not avoid to occur in the actual implementation given that for one village with more than 100 farmers there are typically 4 CCEs.

## 9.2 Implications for further research

Based on our findings in Phase 1, we conclude that PBI can improve willingness to pay for insurance products, lower the transaction costs associated with loss verification, and speed up claims settlement, without inducing moral hazard. Equally important, farmers are willing and able to provide smartphone camera data for loss verification themselves. There is hence strong value in doing a full impact evaluation of the revised intervention. As discussed above, we propose focusing in this impact evaluation not only on wheat but also on other crops, including cotton and horticultural crops, and to conduct the evaluation in Haryana and Madhya Pradesh.

The proposed impact evaluation will look at outcomes such as uptake under real market conditions; moral hazard and adverse selection over time (to validate Phase 1); the impact on production decisions relating to high-risk, high-return crops, as well as resilience practices and technologies; and external validity in another state with lower smartphone ownership but more risk exposure (Madya Pradesh). Further, the provision of insurance products for nutritious horticultural cash crops could help promote the production of these types of crops. To the extent that product diversity leads to dietary diversity, we would also explore direct effects of insurance provision on nutritional outcomes as a human capital investment.

The proposed project has further potential in terms of scalability given the current roll-out of the new Indian insurance program PMFBY. We are currently organizing seminars and workshops with Indian policy makers to present to them this innovative product and jointly evaluate with them under what circumstances PBI could be adopted by the PMFBY. Being rolled out in that entity is the most promising way to scale up in the case of India, because it is difficult for any insurance product to compete with these heavily subsidized schemes. Assessing uptake and valuation of PBI when offered in the context of the PMFBY offers important questions around farmers' uptake, effects on basis risk, and impacts of this approach, which we will address through future research.

Moving forward, we are planning to process the time-series of pictures and damage assessments in three scalable ways. The first approach is already feasible at a moderate scale. We can and will be using this on a pilot basis within existing insurance schemes. The idea of this approach is to use, like in our formative evaluation, an insurance product with two indices: (i) a standard low-cost index, for instance a weather index or a coarse area-yield index measured at for instance the block (instead of village) level; and (ii) damage estimates from visual inspection by experts. The main difference with our formative evaluation approach to make this scalable is that the pictures will be assessed only in case the first index does not trigger a significant payout, and only for farmers who report experiencing visible damage that can be verified from the smartphone pictures. A no-claims discount for the purchase of the product in future seasons will be used to prevent farmers from reporting false claims. The labor cost of picture-based loss assessments in a reasonable time window is only about Rs. 15 per claim, or 0.115% of the sum insured in our pilot products, making this approach feasible at scale (e.g. schemes with up to 50,000 acres insured).

Second, the first approach will provide ground pictures and claims data, which will be complemented with weather data, georeferenced yield data and satellite observations of insured plots. These can be used as training or calibration data for machine learning algorithms and crop models to automate claims processing, which will decrease cost and improve speed of damage assessments even further. Vegetation and texture indices will be derived from the pictures throughout the season (c.f. the PhenoCam project, see Hufkens *et al.*, 2016 and Richardson *et al.,* 2017). Based on these data and weather data, we can use crop growth models to better predict both visible damage and non-visible crop damage from extreme weather events during sensitive growth stages (Leblois & Quirion, 2013).

It is important to note that the development of machine learning algorithms requires a large amount of data to train reliable models. Thus, to be able to implement and validate this approach, and evaluate the accuracy of such indices against objectively measured yields, we are scaling up implementation to cover 5,000 farmers in this upcoming Rabi 2017/18 season, and will in parallel, as data are coming in, apply these tools to further improve our indices. We are working with both academics and the private sector towards index development. On the one hand, phenologists from the Phenocam project mentioned earlier, together with a team of crop modelers from the University of Manchester and the University of Maryland, are applying to our data their research methods for near-surface remote sensing and crop modeling to estimate the effects of weather events on yields. Any tools coming out of this collaboration will become available in the public domain.

We have also started collaborating with a private sector advisory, BKC WeatherSys, to facilitate index development at a faster pace with a stronger focus on pragmatic applications. BKC is the oldest weather company in India, and WeatherSys—it's advisory arm—uses satellite imagery, weather data, plot-level characteristics and crop models to forecast and estimate yields, and to provide advisories. They will integrate the pictures into their crop models to improve yield forecasting and estimation, and they will be able to directly apply this method within their existing advisory services and ICT tools. Further, they have a large user base in the study area, and by providing advisories based on uploaded pictures, they can provide farmers with a direct incentive to upload pictures on a regular basis. This allows us to further increase the availability of training data, for a wide variety of crops, even among uninsured farmers and for crops that are currently not covered through the major insurance schemes.

## 10. Major challenges and lessons learnt

The formative evaluation yielded the following lessons learnt. A number of aspects worked well during the first phase. For instance, although we had doubts initially about the feasibility of providing insurance coverage under the condition of having to take pictures, farmers were very enthusiastic about this approach and indicated that this helped them improve crop management. Further, we did not find the condition to reduce insurance demand during the willingness to pay study. As another example of aspects that worked well, we noted that the loss assessments by experts were consistent with one another, with high correlations across experts for the same sites (that is, high intra-farmer correlations across experts). The consortium collaboration was also successful: it was pragmatic, without major departures from the original proposal or timelines, and we have full faith in each other during the second phase. Finally, we experienced a strong interest from policymakers and practitioners. Although we are still refining the product and automating loss assessment, there is strong buy-in, and we anticipate being able to collaborate with, or provide support to, practitioners in different regions of the world in piloting the PBI approach.

We also faced a number of challenges. First, challenges with the app prevented farmers from taking as many pictures as we would have liked. There were initial issues with the accuracy of GPS measurement and with installation on older versions of Android, with older versions of Google Play Services. There was also no function built into the app that would remind the farmer to take pictures, or provide alerts that there were no pictures being sent. We have now developed a more robust application, which can be installed on a variety of systems, including older versions of Android and older versions of Google Play Services. Further, to address GPS accuracy problems, the developer is building a view frame algorithm that verifies the validity of repeat pictures not only based on GPS coordinates (which can be measured with noise), but also information from the built-in compass (to establish direction in which the phone is held), the accelerometer (to establish the position of the phone) and that tests whether fixed objects in the background of the initial picture, identified through image recognition techniques, appear in the same location in repeat pictures. In-app reminders and other measures to better communicate directly with the farmers are also being incorporated in the more robust app, and in-app reminders will incorporate systematic guidelines that minimize the number of pictures required while optimizing loss assessment, from analyses of Rabi 2016/17 and 2017/18 data.

nalyze the number of pictures required during critical crop growth stages, and the time of the day, to get accurate damage estimates; and these findings can be used to set systematic guidelines during Phase 2. We can then use these guidelines to program smart reminders in the app that ask farmers to take only the minimum number of pictures required for optimal damage assessment. We have added this in the section on lessons learnt.

Second, there were a number of document requirements for claims processing, which burdened both staff and farmers. One of the features of the product that farmers initially valued was that enrolment was hassle-free: there was no need to provide land ownership certificates, for instance. At the time of claims processing, HDFC requested such information, but moving forward, the consortium has decided that with the initial picture being geo-referenced, there is no need to collect such information. Other documents that needed to be collected at the time of claims processing, which farmers were willing to provide without hesitation, will already be requested from farmers at the time of enrolment.

A third challenge was related to the quality of the WBI product, and the insurance education around this product. Of all farmers in villages that were randomly assigned to receive the WBI product, about 50% said ‘yes’ to the question whether they thought their insurance product was covering them for visible damage in the smartphone pictures. Although in general, survey respondents are inclined to respond ‘yes’ to these types of questions, and although in the treatment group with PBI coverage the percentage responding ‘yes’ to this question was significantly higher, we do believe that 50% is too high and indicative of poor understanding. This was most likely due to miscommunication during the training around the reasons for why these farmers had to send pictures through the smartphone app (for research purposes). Hence, moving forward, we will only condition picture-based insurance coverage on the regular submission of smartphone camera data, and we will invest more heavily in insurance education.

A fourth challenge encountered is that the willingness to pay for the WBI product—and hence the WBI component in the bundled WBI and PBI product—was too low to offer the bundled product under real market conditions, without premium subsidies. This could be in part due to the timing of the study. In order to meet the deadline of the formative evaluation, we had to carry out the willingness to pay (WTP) experiments in August, well before land preparation for the wheat crop. Thus, risk in wheat production may not have been very salient at this time, and farmers may have preferred to wait until after the Kharif harvest before deciding to purchase insurance for the next season. In addition, we elicited the WTP when farmers were already making production decisions for Kharif season. This may have led to farmers being more liquidity constrained when deciding about their willingness to pay. A final reason for the relatively low willingness to pay for the WBI product is that wheat is considered to be less risky compared with other crops that farmers in Haryana and Punjab can produce. Therefore, in Phase 2, we will (i) develop products for other crops, (ii) develop an add-on PBI product to the already subsidized PMFBY instead of our own non-subsidized WBI product, and (iii) provide promotional discounts to encourage initial uptake of the add-on product.

## Appendix A: Village Statistics

| | Sample Frame Villages | | Sample Villages | | | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Diff | p-value |
| **Panel A** | (1) | (2) | (3) | (4) | (5) | (6) |
| Total Population (thousands) | 1.65 | 2.876 | 1.723 | 1.296 | 0.073 | 0.8593 |
| Total Male (thousands) | 0.964 | 2.394 | 0.952 | 0.679 | -0.012 | 0.9721 |
| Total Female (thousands) | 0.706 | 0.794 | 0.778 | 0.637 | 0.072 | 0.5331 |
| Distance | 3.175 | 1.136 | 3.06 | 1.405 | -0.115 | 0.4969 |
| **Panel B (%)** | | | | | | |
| Population Belonging to Scheduled Caste | 0.335 | 0.159 | 0.313 | 0.155 | -0.022 | 0.3538 |
| Total Population that is Illiterate | 0.347 | 0.085 | 0.346 | 0.081 | 0.000 | 0.9809 |
| Population who are Cultivators as Main Occupation | 0.117 | 0.052 | 0.121 | 0.053 | 0.004 | 0.5545 |
| Population who are Marginal Cultivators | 0.007 | 0.018 | 0.007 | 0.015 | 0.000 | 0.8703 |
| Population who are Agricultural Labourers as Main Occupation | 0.059 | 0.047 | 0.057 | 0.042 | -0.003 | 0.6911 |
| Population who are Marginal Agricultural Labourers | 0.008 | 0.02 | 0.01 | 0.02 | 0.002 | 0.5972 |
| **Panel C** | | | | | | |
| Males that are Illiterate | 0.31 | 0.075 | 0.305 | 0.068 | -0.006 | 0.5987 |
| Males who are Cultivators as Main Occupation | 0.177 | 0.093 | 0.179 | 0.101 | 0.002 | 0.9112 |
| Males who are Marginal Cultivators | 0.006 | 0.013 | 0.005 | 0.01 | -0.001 | 0.792 |
| Males who are Agricultural Labourers as Main Occupation | 0.032 | 0.061 | 0.037 | 0.067 | 0.005 | 0.6059 |
| Males who are Marginal Agricultural Labourers | 0.01 | 0.023 | 0.011 | 0.023 | 0.002 | 0.6335 |
| **Panel D** | | | | | | |
| Females that are Illiterate | 0.795 | 1.144 | 0.888 | 1.311 | 0.093 | 0.5832 |
| Females who are Cultivators as Main Occupation | 0.054 | 0.173 | 0.078 | 0.209 | 0.025 | 0.3408 |
| Females who are Marginal Cultivators | 0.023 | 0.119 | 0.016 | 0.04 | -0.007 | 0.6795 |
| Females who are Agricultural Labourers as Main Occupation | 0.004 | 0.015 | 0.002 | 0.007 | -0.002 | 0.4643 |
| Females who are Marginal Agricultural Labourers | 0.034 | 0.119 | 0.036 | 0.099 | 0.002 | 0.8999 |

Note: This table presents a balance test to see whether our sample villages are statistically different from our sample frame villages. We see that there is no statistically significant different across population variables, occupational variables, and literacy. This data comes from the Census of India.

## Appendix B: Inputs to Production

| | Mean | SD | Median | Min | Max | N |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Totals* | | | | | | |
| Fertilizer (Kgs/acre) | 115.91 | 23.791 | 111 | 50 | 250 | 727 |
| Pesticides/Herbicides (g/acre) | 560.899 | 340.875 | 500 | 0 | 2500 | 736 |
| Labor (days) | 45.066 | 34.844 | 40 | 0 | 360 | 731 |
| Irrigation (applications) | 2.861 | 1.547 | 3 | 0 | 10 | 736 |
| *Panel B: Fertilizers (Kgs/acre)* | | | | | | |
| Urea | 48.063 | 11.139 | 50 | 3 | 100 | 735 |
| DAP | 61.141 | 17.137 | 50 | 0 | 100 | 736 |
| Potash | 4.363 | 12.28 | 0 | 0 | 100 | 735 |
| *Panel C: Pesticides/Herbicides(g/acre)* | | | | | | |
| Pesticides | 286.539 | 235.445 | 250 | 0 | 1500 | 736 |
| Herbicides | 274.36 | 214.344 | 200 | 0 | 2000 | 736 |
| *Panel D: Labor (Days/acre)* | | | | | | |
| Hired Male Labor | 11.34 | 31.074 | 4 | 0 | 300 | 734 |
| Hired Female Labor | 0.223 | 1.297 | 0 | 0 | 20 | 735 |
| Days of Own Labor | 28.09 | 17.829 | 20 | 0 | 100 | 736 |

Notes: All values are baseline values. These include fertilizers, pesticides, and herbicides, all normalized to per acre-per application values. Labor is normalized to a per-acre value for the entire season.

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