The Feasibility of Picture-Based Insurance (PBI)

Smartphone Pictures for Affordable Crop Insurance

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The Feasibility of Picture-Based Insurance (PBI): Smartphone Pictures for Affordable Crop Insurance

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Abstract
Smallholder farmers are increasingly exposed to weather extremes but lack access to affordable insurance products to protect their livelihoods from catastrophic crop damage. This paper analyzes the feasibility of Picture-Based Insurance (PBI) as a tool to improve the quality and affordability of crop insurance. Under PBI, insurance claims are verified using a time-lapse of pictures from insured plots, both pre- and post-damage, taken by farmers themselves using regular smartphone cameras. PBI aims at minimizing asymmetric information and costs of claims verification compared to indemnity insurance, while reducing basis risk and improving trust, tangibility, and understanding compared to index-based insurance. A pilot implementation in the rice-wheat belt of India speaks to PBI being a feasible and valuable complement to existing insurance products. Damage is visible from smartphone pictures, farmers can take pictures of sufficient quality for loss assessment, and PBI helps reduce severe downside basis risk at minimal cost.

JEL codes: G220, O13, O16, Q14

Keywords: risk and insurance; mobile technology; basis risk; India

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1. Introduction

Climate change is increasingly exposing smallholder farmers to natural hazards such as drought, heat, excess rainfall, hail, or pests and diseases (Porter et al., 2014), while the supply of reliable indemnity insurance coverage against weather extremes remains limited. In particular, two factors contribute to making indemnity insurance premiums unaffordable. First, the amounts that smallholder farmers seek to insure are small relative to the transaction costs associated with providing insurance. Second, asymmetric information between farmers and insurance providers can lead to adverse selection and moral hazard (Hazell et al., 1986). The lack of reliable formal risk-management instruments, in turn, leaves smallholder farmers’ livelihoods vulnerable to extreme weather shocks, limiting risk averse farmers’ willingness to invest in productivity-enhancing technologies and hampering investments in the production of profitable crops (Barrett and McPeak, 2006; Cai, 2013; Cai et al., 2009; Cole et al., 2017; Dercon and Hoddinott, 2004; Karlan et al., 2014; Mobarak and Rosenzweig, 2012).

In the past few decades, various index-based insurance products have been piloted as a potential solution to the high transaction costs and information asymmetry problems that challenge indemnity insurance. Index-based insurance pays out according to a predetermined index, which proxies for losses resulting from weather and other catastrophic events. By determining insurance payouts through an objective index such as the amount of rainfall or the average temperature, insurance providers eliminate asymmetric information and do not need to send claim adjusters to assess damage on individual fields, reducing the cost of claim verification and the time until claim settlement. Yet, demand for such index-based insurance products has been low, even when offered at subsidized premiums, due to limited trust in insurance providers, a lack of understanding of these insurance products, and high levels of basis risk, meaning that indices and associated insurance payouts often do not correlate well with plot-level damage (Cole et al., 2013; Hill et al., 2016; Matul et al. 2013; Mobarak and Rosenzweig, 2012).

This paper describes a new approach to overcome these challenges: Picture-Based Insurance (PBI). PBI provides insurance coverage for damage detected from a time-lapse of the insured crop, built from both pre- and post-damage georeferenced pictures that farmers can take themselves using regular, low-cost smartphones. This approach allows farmers to reliably document damage after a natural calamity, while providing evidence that the crop was managed appropriately until that
point. This can help reduce information asymmetries and lower the costs of plot-level loss verification that have challenged traditional indemnity insurance. At the same time, by being participatory and tangible, and by delivering plot-level assessments of damage, PBI has the potential to reduce basis risk and improve trust and understanding, key challenges for index-based insurance schemes.\(^1\) As such, PBI is designed to combine key advantages of both index-based insurance—timely compensation without expensive loss assessments—and indemnity insurance—minimum basis risk and a tangible product.\(^2\)

PBI is a novel concept that has not been tested before in a systematic way. In this paper, we therefore address key knowledge gaps around the feasibility and applicability of PBI. We describe the implementation and results of a formative evaluation of PBI that targeted 750 smallholder wheat farmers in Haryana and Punjab, two states in northwest India. The feasibility study was designed to answer three research questions: (i) to what extent are farmers willing to participate in PBI by regularly uploading georeferenced pictures of their plots, and how is participation linked to traditional determinants of technology acceptance such as age, education, and caste; (ii) to what extent is damage visible in smartphone camera data, that is, do images that smallholders take using their own phones contain visible characteristics that are predictive of crop damage; and (iii) does PBI reduce basis risk, meaning that PBI offers improved protection against crop damage, compared with conventional weather-index insurance products?

Overall, the results speak to PBI being a feasible and valuable option to complement and improve upon existing index-based insurance products. We find that farmers are able and willing to use the smartphone application and upload enough pictures of sufficient quality for loss assessment. Damage is visible from smartphone pictures and can be quantified by local expert agronomists. Importantly, picture-based damage estimates are strongly correlated with yields and perform substantially better than weather-based indices. We also conduct simulations showing that PBI is a cost-effective add-on to reduce downside basis risk in the context of an area yield-based index,

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\(^1\) PBI can reduce 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 some pests and diseases, and lodging, as opposed to only weather-related events (reducing design basis risk); and by following farmer-specific timing in terms of planting time and the individual seed’s crop cycle instead of the average risk profile for the crop (reducing temporal basis risk).

\(^2\) The closeness to indemnity insurance, however, may potentially come at a cost if it leads to the reintroduction of information asymmetry problems such as moral hazard and adverse selection, otherwise negligible in index-based insurance products. In this regard, Ceballos and Kramer (2018a and 2018b) find no evidence of, respectively, moral hazard or adverse selection within this randomized control trial.
which is the main type of index used in India’s national crop insurance scheme. Based on these findings, we conclude that PBI offers a promising option to strengthen existing index insurance products for poor farmers.

This innovation comes in a timely manner, as it takes advantage of increased smartphone ownership and improved penetration of low-cost mobile internet services among smallholder farmers. PBI further builds upon recent advances in image processing; particularly on applications that use digital repeat photography for near-surface remote sensing. For instance, in a series of studies that uses canopy pictures from a network of digital cameras across the northeastern United States and adjacent Canada (the PhenoCam project), quantitative color information extracted from pictures—providing information about foliage amount and color—helped improve productivity estimates compared with information derived through satellite remote sensing alone (Richardson, et al., 2017). Insights from the literature on near-surface remote sensing could be applied when designing PBI products.

The PBI approach is part of a larger development of using technological and institutional innovations to improve insurance coverage for smallholder farmers. Technological innovations include the use of high temporal- and spatial-resolution satellite imagery to identify losses at finer scales (Stanimirova et al., 2013). Satellite-based damage estimation, however, can be very expensive and is still subject to shortcomings, such as cloud cover, large computational storage and processing costs, and poor availability of georeferenced cadasters to accurately identify insured plots. Moreover, in most settings, basis risk is still present, due to, for instance, measurement error or intercropping practices. PBI can tackle many of the issues above. By placing ‘eyes on the ground’, smartphone pictures can provide a wealth of additional information visible only at ground-level, such as the standing of the crop or the presence of specific pests, diseases, and other subtle features indicating damage by hail or suboptimal temperatures (Hufkens et al., 2019). As such, PBI can stand as a valuable tool to complement and strengthen increasingly popular remote sensing products.

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3 These are sometimes combined with participatory community meetings to validate product design and improve farmer engagement and overall take-up (Carter et al., 2008; Chantarat et al., 2013).
Other innovations involve adding an extra layer of protection on top of a traditional index product, such as fail-safe index insurance or gap insurance (Berhane et al., 2015; Flatnes and Carter, 2015), which allows for audit-based payouts if the index does not trigger but a sufficient proportion of farmers in an area claim to have suffered losses. A key challenge in delivering gap insurance is that there is no documentation of pre-damage and pre-audit crop conditions. As such, PBI can help operationalize gap insurance, with pictures of insured crops serving as a fail-safe trigger, that is, as input for audits when farmers report losses despite the index not having triggered. If further integrated into existing insurance products, PBI can also help reduce upside basis risk, making insurance more affordable, by detecting situations in which the index has triggered a payout while there is no visible indication of crop damage. Finally, while the proposed approaches rely on auditing average losses at a reduced geographic level, basis risk stemming from very localized perils may remain, and PBI can help address this issue.

The paper is structured as follows. The next section discusses the study context and procedures. Section 3 describes the different data sources used in subsequent analyses. Section 4 reviews the available evidence for each of the questions presented above. Section 5 provides concluding remarks and avenues for future research.

2. **Context and Procedures**

In this section, we provide more information on the context of the feasibility study and the procedures that were followed. We first describe the study region in which we conducted the formative evaluation, as well as the sampling procedures used to identify study participants. We then describe the insurance products that were tested as part of the study, including the PBI product and the weather index-based product that was used for comparison purposes. The final part of this section provides a detailed description of the study procedures.

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4 A third but not mutually exclusive idea has been to shift focus from individual farmers to farmer associations or producer groups (de Janvry et al., 2014; Dercon et al., 2014) and to financial institutions (Carter et al., 2016). 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 advantage of such a system is that individual (idiosyncratic) negative and positive basis risk could largely offset each other in the aggregate portfolio. The question though remains on the extent to which these benefits trickle down to the actual farmers beyond the loan write-off, particularly for those affected the most by the shock.
2.1 Study Context and Sampling

The study was conducted for wheat grown during the Rabi (winter) season in the states of Haryana and Punjab. These states 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 heatwaves due to climate change. We selected this region for a proof of concept in part due to this increasing exposure to weather risks, and in part due to near-universal ownership of smartphones among farmers ownership, with smartphone penetration still gaining momentum in other parts of India, where less than 40 percent of mobile phone users has a smartphone.5

Within these two states, the study targeted six districts (three from Punjab, two from the west of Haryana and one from the northeast of Haryana) for which the underwriter of the insurance products, HDFC Ergo General Insurance Limited, could source rainfall and temperature data from weather stations, to allow for comparisons of PBI and weather index-based insurance. From a list of available weather stations, we randomly selected 25 stations stratified by district, with the number of weather stations per district (ranging from three to eight) being proportional to district size. Subsequently, we randomly selected two rural villages within a radius of five kilometers from each weather station (to limit geographical or spatial basis risk), subject to the condition that the village had at least 40 households, 40 main cultivators, or a total population of over 140 individuals during the 2011 Indian Agricultural Census (to capture enough farming households within each village).6 This resulted in a total of 50 villages to be included in the study.

In each village, we conducted a listing exercise of all farming households and randomly selected—among those owning a smartphone and planning to grow at least two acres of wheat during the upcoming Rabi season—15 farmers per village for a baseline survey. These farmers

5 According to data available online, https://www.statista.com/statistics/257048/smartphone-user-penetration-in-india/. Wheat was selected because nearly all farmers in the selected districts grow this crop, whereas there is more heterogeneity in the production of the kharif (monsoon) crop. Moreover, because agriculture is largely irrigated in Haryana and Punjab, the main risk during the monsoon season—a drought or late onset of the monsoon—does not affect production as much as it does in states relying on rain-fed agriculture. Wheat is, however, considered a relatively safe crop in these states, which may reduce the need for insurance and thus reduce the incentives to comply with the picture-taking protocol. While we find a high level of participation (see below), PBI may be better-suited to riskier crops in the region, such as fruits, vegetables or cotton.
6 Weather stations with fewer than five such villages were excluded from the sampling frame.
were equally distributed across three categories: operating less than five acres, operating five to ten acres, and operating ten to fifteen acres of farmland. Our focus on relatively smaller farmers was motivated by external validity considerations. Representative farmer populations in other states of India have typically smaller landholdings than farmers in Haryana and Punjab. In addition, the PBI approach appears more valuable and relevant for these smallholder farmers than for larger ones. Since an overview smartphone picture is limited in the extent of the field it can capture, the approach seems inviable for large farms with multiple, extensive plots. Larger farmers are also more likely to have sufficiently large plots with homogenous land cover for high-resolution satellite imagery to capture plot conditions.

2.2 Insurance Products

All farmers in the baseline survey were offered insurance, free of charge, for one acre of their wheat crop grown during the Rabi 2016/17 season (spanning November through April). In all 50 study villages, the product included a weather index-based insurance component (WBI), which triggered payouts in case of unseasonal rains or above-normal temperatures between February and April (around flowering and harvest time). The indices relied on daily minimum temperature and rainfall collected at the nearest weather station, and were developed based on focus group discussions with farmers and key informant interviews with local wheat agronomists. For each index, payouts were triggered once the index exceeded a strike value, which was set to rounded values of the 70th percentile of the historical records for one weather station in Haryana (for the two western districts in Haryana) and one weather station in Punjab (for the study districts in Punjab and one district in northeastern Haryana), and payouts were linearly increasing in the index until reaching an exit value, set to the 99th percentile. For index levels at or above the exit value, farmers would receive the total sum insured. The WBI product would make payments for either the rainfall or the temperature index, whichever triggered the highest payout.

The sum insured for this product was 13,000 Indian Rupees (Rs.) or, at the prevailing exchange rate of Rs. 65 per USD, 200 US dollars per acre. This amount was based on the average total production costs for one acre of wheat, including labor, as determined during the initial focus group discussions. The cost of this stand-alone WBI product was Rs. 3,133 (incl. taxes) in Punjab and the northeastern Haryana district, and Rs. 3,149 in the two western Haryana districts. The premium was relatively high, at 24% of the insured sum, for two reasons. First, given that the
trigger was set to the 70th percentile of historical index values, both the excess rainfall index and the above-normal temperature index were designed to trigger once every three or four years. Second, this non-subsidized premium included a relatively high loading factor (the insurance premium minus expected payouts) of approximately 50%.

For every weather station, we randomly selected one of the two villages—or 25 villages in total—to receive in addition to the WBI component a picture-based insurance component (PBI), which provided coverage against visible damage in pictures taken throughout the Rabi season. Farmers from these 25 PBI villages were informed that to determine payouts, independent experts would inspect their pictures for visible damage due to risks beyond their control. In the absence of existing loss assessment algorithms, this procedure was transparent and acceptable to participating farmers. Farmers were told that damage below 20 percent would not trigger payouts; damage between 20 to 50 percent would trigger a payout of Rs. 3,900; damage between 50 and 75 percent would trigger a payout of Rs. 7,800; and damage above 75 percent would trigger the maximum PBI payout of Rs. 13,000. PBI payouts were hence a percentage of the sum insured, based on the average production cost per acre, and market prices did not determine insurance payouts. Farmers would receive a payout for either the WBI or the PBI component, whichever triggered a higher payout. In the remaining 25 WBI villages, farmers received payouts for only the WBI component.

Adding PBI coverage increased the cost of the insurance product by approximately Rs. 630 (or 20 percent) to Rs. 3,760 in the western Haryana and Punjab districts and Rs. 3,779 in the northeastern Haryana districts. This increase in cost reflects the increased probability of payouts for risks not covered under WBI, including damage due to lodging, hailstorms, pests and diseases, and wild animals. Further, underwriting the PBI component was relatively expensive due to a lack of historical yield data to assess yield risk at the individual farmer level. Additional costs associated with PBI coverage, notably the data management and loss assessments by independent experts, were not included in the insurance premium but borne by the project. At current expert consultancy rates of Rs. 35,000 per month and assuming an assessment takes about 10 minutes per claim, one expert would be able to verify 960 claims per month, resulting in an approximate cost of Rs. 36.50

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7 We randomized the type of insurance product offered to farmers in order to test whether PBI affects farmer behavior. The findings from that behavioral experiment are discussed in Ceballos and Kramer (2018a). They find no evidence of moral hazard, which might be in part due to the systematic picture-taking protocol that farmers needed to follow in order to maintain their insurance coverage.
per assessment, or—assuming only 20% of farmers file a claim and three experts review each case—an estimated Rs. 21.90 per policy (around 0.34 U.S. dollars). Thus, although the cost of loss indemnification is a variable cost, it amounts to a negligible 0.17 percent of the sum insured.

2.3 Procedures

During July and August 2016, we conducted a baseline survey among the 15 selected farmers in each of the 50 study villages. In October 2016, we invited these farmers to village sessions in which they were informed that they would receive—free of charge—a agricultural insurance for one acre of their wheat crop for the upcoming Rabi growing season. All in all, 592 farmers (approximately 12 per village) agreed to provide crop pictures, of which 296 farmers from the 25 WBI villages received the WBI product, with the remaining 296 farmers from the 25 PBI villages receiving the combined WBI and PBI product. While only this latter group of farmers was insured for damage visible in their smartphone pictures under PBI, all farmers were told that their WBI coverage would be conditional on following the picture-taking protocol during the entire season.

The protocol for taking pictures entailed capturing repeat photographs of the same portion of a randomly selected field (i.e. a site) three times a week throughout the entire growing season, using a smartphone application named WheatCam, which was designed specifically for this purpose. In determining the number of pictures required to reliably identify and estimate damage, we considered two perspectives. On one hand, loss assessment experts indicated that losses could be quantified from irregular, infrequent pictures showing the development of the wheat plant at a few different growth stages (to rule out mismanagement) in addition to a few pictures at the time of damage and immediately before harvest (to quantify the nature and level of the loss). On the other hand, one of our future objectives—using the data from the 2016/17 pilot and future seasons as labeled data to train image processing algorithms and automate damage assessment (Hufkens et al., 2019)—required ideally 30 pictures per site (roughly equally distributed across the season), implying larger data requirements than those for visual inspection.

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8 Due to technical problems in the initial roll-out of the WheatCam app, it was later decided to relax this criterion, and to consider farmers for insurance payouts if they had taken at least 2 pictures throughout the season.
9 Hufkens et al. (2019) extract color information to estimate greenness curves across the entire Rabi season. They use these curves to estimate crop growth stage, which is an important determinant of how weather shocks affect crop yields. This can potentially help reduce basis risk in WBI products. Moreover, greenness curves can provide a proxy for biomass growth, which can be compared with a benchmark for normal growth to assess damage. The number of
Farmers were requested to take their field pictures between 10am and 2pm to maintain appropriate and comparable lighting levels across all images. Farmers were told that pictures had to be taken from the same spot, pointing at the same direction every time. The app facilitated this task through geotags and visual aids. Geotags were used to issue warnings if the repeat picture was being taken at a location different from that of the initial picture. Furthermore, when taking a repeat picture, WheatCam displayed the initial picture as a “ghost” image (a mildly transparent image), allowing the farmer to align static features in the landscape (such as distant trees or structures as well as the reference pole in the field) with those same elements in the initial picture, thus ensuring an almost-identical view frame throughout the season (panel B of Figure 1). To further standardize the time-lapse of field pictures, WheatCam applied a fixed white balance between images, keeping in-camera RGB ratios constant.

**Figure 1. Visual aids for maintaining a fixed view frame through the growing season**

Panel A. Reference and Auxiliary Poles                  Panel B. Ghost image

Note: This figure shows the visual aids used to ensure a fixed view frame when taking repeat pictures at a farmer’s site. Panel A shows the auxiliary pole, serving as a tripod to maintain a fixed position for the phone, and the reference pole, serving as a fixed reference point in the plot. Panel B shows the “ghost” image, consisting of a mildly transparent version of the initial image that allowed the farmer to align static features in the landscape across pictures.

In an initial visit, project staff would download the WheatCam app to farmers’ phones, enter their unique IDs, take an initial picture in randomly selected sites for which farmers would receive pictures required for automated loss assessment could potentially reduce when relying on other image features for identifying damage, such as texture indices or other synthetic features arising from deep learning techniques.
insurance coverage, and train farmers on how to take repeat pictures using WheatCam. Pictures validated by WheatCam were automatically uploaded to a server and processed by the research team. It was not possible to upload pictures taken outside WheatCam, eliminating any possibilities for editing the pictures prior to submission. Farmers could reach out throughout the season to project staff for troubleshooting in case they encountered any problems with the app or protocol.

All farmers who agreed to take pictures were provided with a set of two inexpensive poles: an auxiliary pole, which served as a tripod to help maintain a fixed position from where to place the phone and take the repeat pictures, and a reference pole, which served as a fixed reference in the plot to aid with the framing of the picture (panel A of Figure 1). While the cost of these poles was negligible, at Rs. 170 per set (2.6 USD), this practice will be discontinued moving forward.

Pictures of insured sites were showing sufficient trees and other structures in the background to align repeat pictures and verify that pictures were always taken at the same location without having the reference pole in place.10 Further, due to app compatibility issues with older Android versions in farmers’ phones at the launch of the project, all farmers who had agreed to take pictures were provided with a low-cost Android smartphone, and farmers received a data plan of Rs. 258 per month to upload the pictures, conditional on following the protocol. However, farmers often report having a data plan, suggesting that the provision of smartphones and data plans may not be a crucial implementation requirement and could be discontinued in the future.

At the end of the season, an independent panel of six wheat experts evaluated the time-lapse of pictures and estimated a percentage of crop damage for each of the available plots. Each time-lapse was randomly assigned to three different experts. Assessments were first done by experts individually and the median assessment was used to determine insurance payouts. If, however, large disagreement existed between the experts’ assessments, a final damage estimate was agreed upon through consensus and used to determine insurance payouts. Assessments were anonymous with no access to the farmer’s personal details or type of insurance coverage. Farmers with damage estimates above 20 percent were submitted as claims to the insurance company. Their claims department reviewed the existing evidence and issued payments directly into the farmers’ bank accounts. The insurance company did not reject any claims based on the available evidence.

10 These tasks could potentially be aided in the future by tapping into the capabilities of the different sensors available in inexpensive smartphones together with geolocation.
3. Data

In this section, we describe the primary data sources used in the analyses below. We will also present relevant descriptive statistics of the study population, including observed attrition.

3.1 Data Sources

Baseline and endline surveys were conducted with all available farmers during August 2016 and April 2017, respectively. The baseline survey, targeting a sample of 750 farmers, inquired about an array of farm and household characteristics, including plot characteristics, cultivation practices, input use, agricultural technology adoption, household composition, income and risk perceptions. The endline survey, targeting the same sample of 750 farmers, gathered data for the Rabi 2016/17 season during which farmers received insurance coverage to gain insights into the feasibility of PBI. Survey questions covered cultivation practices, input use and self-reported wheat yields, perceptions about the insurance product received, and experiences with the WheatCam app.

To obtain an objective measure of wheat yields for our season of interest, we carried out crop cutting exercises (CCEs) at all sites in which a farmer had taken at least two pictures over the season. This is one of the most accurate ways available for estimating plot-level yields.\(^\text{11}\) At each site, research assistants selected two different square meters, both visible in the time-lapse of pictures for the site: one to the left and one to the right of the reference pole. The heads of the wheat plants falling inside these sampled square meters were cut, threshed, and the resulting grain was weighed. We use the average weight from the two square meters from the same site to determine a final yield estimate for a given site.\(^\text{12}\) The CCEs were carried out right before harvest, during the first half of April 2017. CCEs were not used to determine insurance payouts, and farmers were only informed about our efforts to conduct CCEs on the day itself.

Finally, the analyses will use the expert assessments of visible damage in the time-lapse of wheat pictures for each site. As discussed above, once the Rabi season was over and the time-lapse of pictures had been processed and cleaned, each crop site was individually reviewed by three wheat

\(^{11}\) An improved way for estimating plot-level yields, considered to be the “gold standard”, is to harvest the entire plot, which was logistically and financially infeasible in our project. See Lobell et al. (2018) for a complete discussion.

\(^{12}\) It is common agronomic practice to sample larger areas than one square meter to improve the precision of yield estimates. Yet, we find very high correlation between yield estimates for the samples to the left and to the right of the reference pole, and the two measures almost always overlap when discretizing yields into categories. This indicates that the implemented procedure was sufficiently precise for our objective.
experts. For each site, the experts would assess whether the crop was damaged. If the crop was damaged, they would also indicate the loss percentage, the cause of the damage, and in which picture the damage could be first observed. In addition, each expert indicated what percentage of the visible damage was due to unavoidable hazards or due to mismanagement by the farmer. Finally, for those sites in which experts disagreed substantially on the amount of damage, the experts jointly discussed the assessments and reached a consensus about the loss percentage.

3.2 Descriptive Statistics

Table 1 summarizes baseline characteristics across different sub-groups of study farmers. The first column includes all 736 farmers who completed a baseline interview. They are representative of farmers planning to cultivate at least two acres of wheat during Rabi and owning a smartphone in the selected villages from our six study districts in Haryana and Punjab.

The average farmer in our sample is 39 years of age, cultivates about 9 acres of land, and lives in a household of around 6 individuals. Further, 44 percent of farmers have completed tertiary education and 10 percent belong to a scheduled or other backward caste. On average, 94 percent of farmers own the insured plot. They obtain 84 percent of their income from crop cultivation, and wheat represents close to 40 percent of their annual crop income. Average wheat yields are 19.6 quintals per acre and farmers cultivate wheat during the Rabi season in nearly all plots. Finally, more than three quarters of farmers are used to taking pictures with their smartphones and report having regular network signal in their plots.

The second column describes farmers who participated in the project and took at least two pictures throughout the season, thus qualifying for the expert loss assessments. The number of farmers actively taking pictures was 467, which is considerably lower than the number of farmers interviewed at baseline (736 farmers in total). Nevertheless, nearly two thirds of all farmers qualified for loss assessment, and compliance does not seem to have been related to observable farmer, household, or farm characteristics, with any differences being economically small and statistically insignificant, as shown in the third column.

Finally, the fourth column includes the sample of 361 farmers for whom we conducted not only a loss assessment but also were able to conduct the crop cutting experiments. Attrition in the crop cutting experiments is largely due to farmers having harvested already before the team reached a
Table 1. Descriptive statistics and attrition

|                          | (1) Completed baseline | (2) Qualified for loss assessment (LA) | (3) Difference (2) – (1) | (4) Completed LA and CCE | (5) Difference (4) – (1) | (6) Difference (4) – (2) |
|--------------------------|------------------------|---------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| PBI village              | 0.503                  | 0.467                                 | -0.036                   | 0.462                    | -0.041                   | -0.005                   |
|                          | (0.071)                | (0.074)                               |                          | (0.076)                  |                          |                          |
| Age (in years)           | 39.143                 | 39.364                                | 0.221                    | 39.423                   | 0.280                    | 0.059                    |
|                          | (0.722)                | (0.759)                               |                          | (0.814)                  |                          |                          |
| Completed tertiary education | 0.438                  | 0.443                                 | 0.006                    | 0.420                    | -0.017                   | -0.023                   |
|                          | (0.019)                | (0.022)                               |                          | (0.024)                  |                          |                          |
| Belongs to sched./OB caste | 0.102                  | 0.077                                 | -0.025                   | 0.067                    | -0.035                   | -0.010                   |
|                          | (0.029)                | (0.027)                               |                          | (0.028)                  |                          |                          |
| Landholdings (hectares)  | 8.845                  | 8.937                                 | 0.092                    | 8.990                    | 0.144                    | 0.052                    |
|                          | (0.181)                | (0.212)                               |                          | (0.251)                  |                          |                          |
| Household size           | 6.240                  | 6.156                                 | -0.084                   | 6.132                    | -0.109                   | -0.025                   |
|                          | (0.119)                | (0.140)                               |                          | (0.157)                  |                          |                          |
| Perception of yield variability | 3.993                  | 4.073                                 | 0.080                    | 4.073                    | 0.080                    | 0.000                    |
|                          | (0.088)                | (0.094)                               |                          | (0.096)                  |                          |                          |
| Share of income from crops | 0.835                  | 0.842                                 | 0.008                    | 0.845                    | 0.010                    | 0.002                    |
|                          | (0.012)                | (0.013)                               |                          | (0.015)                  |                          |                          |
| Share of crop income from wheat | 0.376                  | 0.383                                 | 0.008                    | 0.389                    | 0.013                    | 0.005                    |
|                          | (0.010)                | (0.012)                               |                          | (0.013)                  |                          |                          |
| Fraction of land planned to be sown with wheat | 0.961                  | 0.965                                 | 0.003                    | 0.969                    | 0.008                    | 0.004                    |
|                          | (0.007)                | (0.007)                               |                          | (0.006)                  |                          |                          |
| Wheat yield Rabi 2015/16 | 19.570                 | 19.556                                | -0.015                   | 19.568                   | -0.002                   | 0.012                    |
|                          | (0.156)                | (0.178)                               |                          | (0.196)                  |                          |                          |
| Ever used laser land leveler | 0.707                  | 0.700                                 | -0.008                   | 0.713                    | 0.006                    | 0.014                    |
|                          | (0.038)                | (0.043)                               |                          | (0.046)                  |                          |                          |
| Distance from plot to home (minutes) | 15.900                 | 15.777                                | -0.123                   | 16.545                   | 0.645                    | 0.768                    |
|                          | (1.186)                | (1.385)                               |                          | (1.586)                  |                          |                          |
| Owns insured plot        | 0.938                  | 0.941                                 | 0.004                    | 0.936                    | -0.002                   | -0.006                   |
|                          | (0.011)                | (0.012)                               |                          | (0.015)                  |                          |                          |
| Takes pictures on phone often/very often | 0.774                  | 0.752                                 | -0.023                   | 0.754                    | -0.021                   | 0.002                    |
|                          | (0.025)                | (0.026)                               |                          | (0.029)                  |                          |                          |
| Has network signal often/very often | 0.755                  | 0.756                                 | 0.000                    | 0.754                    | -0.002                   | -0.002                   |
|                          | (0.030)                | (0.032)                               |                          | (0.034)                  |                          |                          |

Note: This table shows the mean value of baseline farmer characteristics across different sub-groups of study farmers. Column 1 includes all farmers who completed a baseline interview, column 2 those farmers who qualified for expert loss assessments, and column 4 those for whom both loss assessment and crop cutting experiments were conducted. Columns 3, 5, and 6 show the results of tests of equality of means between every pair of groups, where none of the differences are statistically significant. *** p < 0.01, ** p < 0.05, * p < 0.10.
village, or the crop not yet having ripened at the time the team reached a village. Nonetheless, the differences between farmers with and without data from the crop cutting experiments are again small and not statistically significant. Overall, these results indicate that the final sample of farmers being used for estimation and product assessment in Section 4 is representative of our target population, with no significant evidence of attrition bias in terms of observable farm and household characteristics.

4. Results

This section reports findings regarding three key knowledge gaps concerning the feasibility of the picture-based insurance approach. First, we discuss whether farmers send in a sufficiently large number of pre- and post-damage crop pictures through the Wheatcam app for reliable loss assessment. Second, we assess whether the smartphone pictures contain visible characteristics that capture damage events, that is, whether damage can be quantified accurately from smartphone camera data or not. Third, we analyze to what extent PBI reduces basis risk compared with alternative index insurance approaches.

4.1 Farmer’s Ability and Willingness to Take Repeat Pictures

A first prerequisite for the feasibility of PBI is that there is sufficient camera data available at the time of loss assessment—whether automated, through image processing algorithms, or manual, through visual inspection by wheat experts— from which to determine the overall damage (if any) suffered by the crop. In the present study, we requested farmers to not only take post-damage pictures but instead to take pictures continuously throughout the season so as to document pre-damage conditions, which may be important in making the system tamper-proof, reducing scope for moral hazard, and allowing for automated damage assessment based on detected crop growth stage and visible damage. For this, farmers need to be willing and able to take pictures of their fields regularly and with a sufficient level of quality.

Out of the full sample of 736 farmers, 592 farmers were trained on using the smartphone app. Of them, 467 farmers (78.9 percent) uploaded at least one (valid) picture during the season (on top of
the initial picture taken at the site). Panel A of Figure 2 shows for this subsample the distribution of the total number of pictures taken per farmer.

**Figure 2. Picture-taking activity**

Panel A. Total number of picture taken by farmer

Panel B. Time of the day at which pictures were taken

Panel C. Number of farmers taking at least one picture per week

Note: This figure shows different statistics of farmer’s picture-taking activity throughout the Rabi 2016/17 season. Panel A shows a frequency histogram indicating the number of farmers that took a certain number of pictures through the season. Panel B shows a frequency histogram with the time of the day at which pictures were taken. Panel C plots the number of farmers that took at least one picture per calendar week across the season.

13 Valid pictures are considered pictures of sufficient quality showing an unobstructed view of the same portion of the selected farmer’s field (including the reference pole) within the growing season of interest (October through April). Most pictures uploaded were valid. Of the 117 farmers without valid pictures, most farmers did not upload any picture. While a number of these farmers claimed to have indeed taken pictures through the Wheatcam app, no pictures were found on the server. The possibility thus exists that a problem with the app prevented these pictures from being uploaded. For the purpose of this study, however, we adopt the conservative assumption that these farmers did not take any pictures. The app has since been revamped and considerable testing has been conducted to avoid issues such as this from occurring in the future.
The large majority (73 percent) took at least six pictures throughout the season—or roughly one picture per month. A comparable number of farmers (80.9 percent) uploaded at least two pictures in 2017 (not shown in Figure 2). More than half of the 467 farmers with at least one picture took pictures twice a month or more, resulting in a high-quality time lapse that can be used to develop image processing algorithms for automated loss assessment.

With respect to the time of the day at which pictures were taken, Panel B shows that around 45 percent of the pictures were taken between 10am and 2pm, indicating that farmers took pictures across a broader range of times than initially requested. This can be explained in part by the fact that most plots are not located close to the farmer’s home, due to which farmers only visit their plots at certain times of the day. Moreover, during the colder months of December and January, fog could strongly reduce the visibility in Haryana and Punjab, especially in the morning time. As a result, farmers often needed to wait until the fog had cleared before taking a picture. Nevertheless, despite initial concerns, pictures taken outside of this time frame have still proven useful for greenness index estimation and for the identification of crop growth stages in related research (Hufkens et al., 2019).

In order to map picture-taking activity over time, Panel C shows 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 and the post-harvest period. In the beginning of the season, participation remained limited because the wheat plant had not started growing yet, and because farmers were facing technical challenges with WheatCam. All in all, while farmers did not follow the requested protocol strictly—in part because of challenges with the app at the beginning of the season—they were able to submit a substantial number of pictures of sufficiently high quality for loss assessment. In this regard, it is important to note that WheatCam did not have any built-in reminders, which could have further helped improve the number of pictures taken.

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14 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. In the focus groups, farmers reported that these technical problems were the main reasons for not taking more pictures. These issues were resolved in later versions of the app.
Finally, we analyze whether farmers’ ability and willingness to take pictures for insurance purposes depends on observable farmer characteristics. Because smartphones could be a relatively unfamiliar technology, and technology acceptance could vary across demographic or socioeconomic dimensions, it is important to analyze whether PBI is more inclusive for specific segments of the population. To that end, we study two types of participation. First, we analyze attendance to village sessions, during which farmers were given more information about the insurance products, to explore which characteristics may determine farmers’ interest in insurance ex-ante. Second, we analyze the number of pictures uploaded conditional on taking at least one (initial) picture (indicating that project staff successfully installed the technology on a farmer’s smartphone), as a proxy for continued participation.

The first column in Table 2 shows the results from an ordinary least squares (OLS) regression using as dependent variable a dummy indicator for whether a farmer attended the village session. Farmers belonging to a scheduled or other backward caste and farmers with smaller households were less likely to participate. Wheat yields from the previous season are also negatively correlated with attending the village session, perhaps related to farming ability (where higher-ability farmers may value insurance less) or to a recency bias (where those farmers who did not recently experience problems with their wheat crops tend to underestimate the probability of future hazards). Interestingly, farmers who perceive wheat yields to be more variable and those more dependent on their crop income were more interested in attending an insurance-related session. Other variables, including farmer size, age, education level, experience with smartphones, and a measure of farmer’s progressiveness (as captured by having adopted laser-land levelling in any of his plots in the past) are not significantly related to the probability of attending a village session.

The remaining columns in Table 2 assess the relationship between a farmer’s characteristics and picture-taking behaviors, conditional on having an initial picture—that is, having WheatCam installed in their phone and having been shown how to use it by field staff. Column (2) focuses on the extensive margin, that is, whether a farmer took at least one repeat picture throughout the season. Columns (3) and (4) show the results from, respectively, Tobit regressions of the number of pictures taken and OLS regressions on the number of pictures taken conditional on taking at least one repeat picture. Finally, Column (5) analyzes an alternative measure for the intensity of
Table 2. Factors related to village session attendance and picture-taking behaviors

|                                | (1) | (2) | (3) | (4) | (5) |
|--------------------------------|-----|-----|-----|-----|-----|
|                                | Attended Vill. Sess. | Took repeat pictures | Number of repeat pictures | No. repeat pict. (cond. taking) | Took at least 10 repeat pictures |
|                                | OLS | OLS | Tobit | OLS | OLS |
| Landholdings (HAs)             | -0.005 | -0.006 | -0.342 | -0.176 | 0.005 |
|                                | (0.004) | (0.004) | (0.273) | (0.283) | (0.008) |
| Age is under 30 years          | -0.030 | 0.046 | 1.164 | -0.649 | -0.028 |
|                                | (0.049) | (0.029) | (2.323) | (2.534) | (0.056) |
| Age is over 50 years           | 0.072 | 0.088*** | 2.240 | -0.146 | 0.052 |
|                                | (0.048) | (0.032) | (2.144) | (2.623) | (0.052) |
| Highest level of education     | 0.015 | -0.005 | -0.412 | -0.249 | -0.004 |
|                                | (0.009) | (0.009) | (0.500) | (0.560) | (0.012) |
| Belongs to sched./OB caste      | -0.182*** | -0.102* | -6.617*** | -4.153* | -2.216** |
|                                | (0.067) | (0.053) | (2.034) | (2.132) | (0.103) |
| Perception of yield variability | 0.016* | -0.006 | -0.699 | -0.523 | -0.005 |
|                                | (0.008) | (0.007) | (0.526) | (0.537) | (0.013) |
| Household size                 | 0.015** | -0.001 | 0.102 | 0.228 | 0.009 |
|                                | (0.006) | (0.005) | (0.349) | (0.405) | (0.010) |
| Takes pictures on phone often/very often | -0.031 | 0.031 | 0.925 | 0.323 | 0.105 |
|                                | (0.049) | (0.028) | (2.499) | (2.699) | (0.063) |
| Has network signal often/very often | -0.011 | -0.038 | -0.638 | 0.884 | -0.034 |
|                                | (0.050) | (0.025) | (3.433) | (3.550) | (0.074) |
| Ever used laser land leveller  | 0.016 | 0.023 | 1.604 | 0.618 | -0.047 |
|                                | (0.037) | (0.034) | (2.552) | (2.767) | (0.057) |
| Wheat yield Rabi 2015/16        | -0.019* | -0.005 | 0.438 | 0.657 | 0.013 |
|                                | (0.010) | (0.006) | (0.548) | (0.509) | (0.013) |
| Share of income from crops     | 0.237** | 0.078 | 2.896 | 0.740 | -0.167 |
|                                | (0.103) | (0.094) | (7.337) | (8.402) | (0.136) |
| Share of crop income from wheat | 0.058 | 0.020 | -1.895 | -6.064 | 0.017 |
|                                | (0.156) | (0.103) | (6.807) | (7.138) | (0.233) |
| Fraction of land planned to be sown with wheat | 0.249 | -0.005 | -20.880 | -19.778 | -0.193 |
|                                | (0.178) | (0.133) | (17.493) | (16.412) | (0.286) |
| Owns insured plot              | -0.100 | -0.025 | -12.347** | -11.233** | -0.244*** |
|                                | (0.064) | (0.068) | (4.892) | (5.470) | (0.082) |
| Distance from plot to home (in minutes) | 0.000 | 0.111*** | 0.102** | 0.003*** |
|                                | (0.001) | (0.038) | (0.046) | (0.001) |       |
| Mean of dep. variable          | 0.757 | 0.929 | 17.94 | 17.94 | 0.555 |
| Observations                   | 715  | 461  | 461  | 403  | 461  |
| R-squared                      | 0.109 | 0.125 | 0.176 | 0.165 |       |

Note: Standard errors, clustered at the village level, in parentheses. We also control for a constant, weather station fixed effects, and dummy variables to indicate PBI villages and villages where payments were conditional on not burning the previous season's crop residue (this condition was orthogonal to the treatment under consideration). We do not present coefficients for these variables here. Columns (2) through (4) are conditional on a farmer taking an initial picture. The variables "Owns insured plot" and "Distance from plot to home (in minutes)" were imputed for 13 missing observations using the mean value of the observed sample. A dummy to account for this imputing is controlled for but not reported. *** p < 0.01, ** p < 0.05, * p < 0.10.
taking pictures, using a dummy variable taking the value of 1 when a farmer took at least ten repeat pictures throughout the season and 0 otherwise.

Overall, the results are consistent across specifications. Belonging to a lower caste is a strong determinant for nonparticipation and reduced picture-taking, both in the intensive and extensive margins. In terms of age, we expected higher technology acceptance and hence higher participation among the youngest tercile of farmers in our sample (those with an age below 30 years), but compared with the middle tercile (those between 30 and 50 years), we also observe higher participation in the oldest age tercile (those above 50 years). Interestingly, farmers who do not own their insured plot tended to take more pictures, perhaps related to the fact that conventional insurance products available in the market are linked to land ownership, while the present study was able to include these farmers. Finally, a puzzling finding is that farmers whose plots are located farther from their homes tended to take more pictures. Although we do not have data to test this hypothesis, this could be related to more established routines for visiting their plots.

In sum, certain common characteristics such as caste and exposure to shocks, found to affect participation and risk-management behavior in other contexts, are also important for PBI adoption. However, other characteristics that we expected to affect technology acceptance and PBI participation, such as farmer’s education or level of experience with smartphones, are not significant determinants of participation. Our initial concern that such farmers would be unwilling to engage with an innovative product through a relative unfamiliar technology seems to be unfounded in this context.

4.2 Do Pictures Capture Damage Events? Can Damage Be Quantified Accurately?

A second prerequisite for PBI to be feasible is that damage arising from different types of hazards is indeed visible at plain sight in a smartphone picture. Our protocol required farmers to take overview pictures of insured plots, taken at a sufficient distance such that a large fraction of the plot as well as structures in the background are visible. We opted for this protocol since close-up pictures could become subject to tampering. However, damage might be less visible in overview pictures, raising the question whether overview pictures can indeed capture damage events.

Initial conversations with local wheat agronomists indicated that overview pictures would be able to capture most—though not all—hazards. Certain events such as lodging (the bending of the
wheat plant due to winds and wet, loose soil), hail, or certain common wheat diseases such as yellow rust would indeed be visible. Other events, such as blight or high temperatures late in the growing season, which can affect grain filling without showing up in the external aspect of the plant, would be much more difficult to identify. Experts also highlighted their ability to differentiate damage due to natural disasters from mismanagement.

Endline survey data indicate that farmers have similar perceptions. Figure 3 summarizes, for different hazards, the extent to which farmers believe that pictures can capture damage to the Rabi wheat crop. Most farmers (more than 80%) believe that damage caused by lodging, hail, and excess rainfall can be “very well” or “fairly well” captured from direct visual inspection of a time-lapse of pictures. Farmers recognize, however, that other events such as high temperatures or pests and diseases may be harder to recognize in this way. Appendix Figure 1 shows that hazards considered to be more visible through smartphone pictures are also the ones that worry farmers the most and occurred—at least during the Rabi 2016/17 study season—most often. These factors suggest that PBI is well suited for minimizing basis risk, at least in the context of our study.

**Figure 3. Perceived visibility of hazards in pictures**

Note: This figure shows farmers answers during the baseline survey to whether different hazards to wheat would be visible in overview pictures (taken from a distance of approximately 5-15 meters).

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15 It is interesting to note that, while many events would not be detectable at plain sight, information about them may still be present in other features of the picture, such as subtle changes in the level of greenness, and number of leaves; features which could potentially be exploited by using image vision techniques and machine learning.
Table 3 summarizes the results of the expert loss assessments and the associated insurance payouts. Panel A shows the percentage of cases for which the assessments triggered a payout, together with the different categories corresponding to the PBI insurance payouts. Nearly 10% of farmers experienced a loss above 20%—thus triggering a payout—according to the visual inspection of pictures by experts. Conditional on the PBI product triggering, the average payout was Rs. 5,200, but most of these cases were assessed to have between 20% and 50% damage, triggering the median PBI payout of Rs. 3,900.

| Mean | Std. Dev. | Median | N |
|------|-----------|--------|---|
| Panel A: Triggering of indices |
| WBI index triggered (%) | 22.8 | - | - | 412 |
| PBI index triggered (%) | 9.0 | - | - | 412 |
| Slightly damaged: 20 – 50% (payout Rs. 3,900) | 6.3 | - | - | 412 |
| Severely damaged: 50 – 75% (payout Rs. 7,800) | 2.4 | - | - | 412 |
| Fully damaged: 75 – 100% (payout Rs. 13,000) | 0.3 | - | - | 412 |

| Panel B: Payout if index triggered (in Rs.) |
| WBI payout | 2,307 | 585.1 | 2,259 | 94 |
| PBI payout | 5,200 | 2,188 | 3,900 | 37 |

Note: This table shows summary statistics of weather-based insurance (WBI) and picture-based insurance (PBI) payouts across all study villages. In WBI only villages, PBI payouts include the hypothetical payouts that would have been made based on experts’ loss assessments of pictures if farmers would have been insured under PBI.

Figure 4 shows a box plot of the expert loss assessments for total damage, including damage both due and not due to mismanagement, ordered by the median assessment within a site. The figure reveals a few interesting patterns. For low levels of damage (with the median estimate of damage below 20 percent), we observe high levels of agreement between experts. For sites where the median damage is zero, most outliers fall below the insurance trigger value of 20 percent, meaning that experts did not reach different conclusions in terms of insurance payouts. For sites with higher levels of visible damage (with the median estimate of damage above 20 percent), we naturally observe more disagreement regarding the exact level of damage. Most experts nonetheless agree on the approximate region in which the damage falls and stark outliers are rare. We interpret this consistency across loss assessments as an indication that the wheat experts can identify crop losses from direct visual inspection of pictures.
Figure 4. Individual expert loss assessments

Note: The figure shows the dispersion of individual experts’ damage assessments across different levels of median damage assessment at a site (where for each crop site there are three expert assessments). A median damage assessment category may contain multiple sites with the same median assessment.

Figure 5. Yields from crop-cutting experiments (CCEs) and expert loss assessments

Note: This figure shows a scatterplot of (a) wheat yields captured during crop cutting experiments (CCE) conducted immediately before harvest and (b) the median damage assessment from wheat experts based solely on the time-lapse of pictures from the entire season. Each observation corresponds to one single plot.
An important question, of course, is whether the damage assessed from pictures corresponds with the actual damage present in the crop. For this, we rely on the crop-cutting exercises (CCEs) carried out at the end of the Rabi 2016/17 season. Figure 5 shows a scatterplot, mapping the yields from the CCEs on the vertical axis against the final expert loss assessment for that field (that is, the joint expert consensus for sites with a lot of disagreement and median assessment for the rest). We are using yields instead of self-reported damage because the former are objectively measured, and not subject to reporting bias. They are however not a perfect indicator of damage; yields are not only determined by the realization of risk but also by characteristics such as management practices, soil quality, and water availability. From an insurance perspective, it is important that the loss assessment identifies plots with severe damage, that is, the sites with very low yields below for instance, 10 quintals per acre (corresponding to 50% damage for the average farmer).

In Figure 5, there is a clear negative relationship between the damage estimated by the experts and CCE yields, suggesting that experts are generally able to identify damage when damage exists. This negative relationship is mainly driven by the extreme values of yields below 10 quintals per acre, which is catastrophic damage for which a multi-peril insurance product should trigger payouts. Table 4 shows for which proportion of farmers with yields below 10 quintals per acre, yields between 10 and 16 quintals per acre, and above 16 quintals per acre, the PBI product triggered payments. The PBI product that was implemented would have triggered payments in 71.4 percent of the 14 cases with yields below 10 quintals per acre.

| Yields: | Picture-based insurance (PBI) | Weather index-based insurance (WBI) | Number of observations |
|---------|------------------------------|-----------------------------------|------------------------|
| High damage: Lower than 10 ql./acre | 0.714 | 0.000 | 14 |
| Medium damage: Between 10 and 16 ql./acre | 0.061 | 0.364 | 33 |
| Low/No damage: Higher than 16 ql./acre | 0.071 | 0.242 | 310 |
| All | 0.095 | 0.244 | 357 |

Note: This table shows the fraction of farmers receiving a payout from the picture-based insurance (PBI) and weather-based insurance (WBI) products by category of damage, based on the wheat yields captured during crop cutting experiments (CCE) conducted immediately before harvest.
Assessments were not as accurate for less extreme yield losses. Experts detected substantial visible damage for 7.1 percent of farmers with normal yields (above 16 quintals per acre), while detecting such damage for only 6.1 percent of farmers with moderate yield losses (yields between 10 and 16 quintals per acre). Poor correlation between assessed damage and measured yields is mainly driven by sites for which the final assessed damage level was equal to zero, which include a number of sites with no visible evidence of damage and with disagreement about whether the visible damage was due to mismanagement by the farmer. In particular, of the four sites with assessed damage under 20 percent and yields lower than 10 quintals per acre (in red in the figure), three did not show any visible damage in the pictures and one showed visible damage which was categorized by the experts as mismanagement of the crop under water-logging conditions. Overall, though, the experts were successful at identifying the farmers with especially severe damage, who would have needed insurance payouts the most, and expert assessments explained a significant 18 percent of the total variation in yields.

4.3 Does PBI Offer Better Protection than Other Insurance Products?

In this subsection, we compare the cost-effectiveness of PBI and alternative index products in terms of their ability to provide comprehensive coverage with minimal basis risk. Doing so, we take the WBI premium as a benchmark, interpreting it as the base rate at which insurance can be provided considering expected payouts for covariate weather-related damage and all back-end administrative costs. During the Rabi 2016/17 season, there was no severe damage due to excess rainfall or extreme temperatures, the two perils covered by the WBI product. Hence, we assume that observed PBI payouts were related to idiosyncratic risks not covered by WBI. This assumption will allow us to compare the incremental costs of providing PBI with the improved coverage in terms of reduced basis risk. We thereby focus on costs in terms of average PBI payouts and abstract from other variable costs—notably the costs of loss assessment, previously shown to represent a negligible 0.17% of the sum insured—and from fixed operational costs—which we assume to be comparable across insurance schemes, especially as these fixed costs get diluted with a larger number of insured sites.16

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16 We also ignore data and hardware (i.e. owning a smartphone) costs since we envision the farmer being responsible for these in a future scale up of PBI.
Table 3 summarized the proportion of farmers for whom the WBI product triggered, and the average payouts in case the product triggered. In contrast to the 9% of farmers for whom the PBI product triggered, WBI triggered payouts for a significantly higher 22.8% 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 2016/17 season. Moreover, the average payout for PBI was higher than that for WBI (Table 3 Panel B). This could be indicative of PBI identifying farmers with substantial damage, resulting in higher payouts, with WBI payouts having triggered more frequently but at relatively low index values.

Figure 6 compares the performance of PBI with that of two types of index insurance: (i) the weather index-based product (WBI) that all study participants received; and (ii) an area-yield product (AYI), which pays out according to the average yield estimated from a limited number of crop-cutting experiments (CCEs) in a given geographic area (such as a village or block in the case of India). Although we did not provide area-yield index insurance coverage in our study, the comparison with such a product is highly relevant. In India alone, the Pradhan Mantri Fasal Bima Yojana (PMFBY, or Prime Minister’s National Crop Insurance Scheme), which was launched in 2015/16 and covered more than 40 million farmers during the Kharif 2017 season, relies mostly on this type of loss assessment mechanism (Bhushan and Kumar, 2017).

The way we approach the AYI product is through simulation, relying on the CCEs yield data collected right before harvest. Specifically, we randomly select four farmers for each (a) district or (b) cluster of two nearby villages (located within five kilometers from the same weather station), use their yields to construct an area-yield index, and assume payouts are triggered (to all farmers in the district or cluster) when the area-yield index is below 16 quintals per acre (20% or more below normal yields). We repeat this exercise 10,000 times and report the relevant average values across these iterations. Finally, we assume that the cost of conducting the CCEs is low relative to the sum insured, hence considering average payouts as the main cost of providing such insurance.17

Figure 6 summarizes the proportion of farmers for whom the PBI and WBI products triggered and the average simulated proportion of farmers for whom the district-level and village cluster-level

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17 In the case of the CCEs conducted at the end of the Rabi 2016/17 season, the average costs for covering one village in approximately one day of work were around Rs. 4,500 (excluding project staff, which we consider a fixed operational cost). Under the reasonable assumption that the above costs would be distributed across at least 100 insured farmers, the cost would be at most Rs. 45 per site, or 0.35% of the sum insured.
AYI products would have triggered. As before, we disaggregate farmers into three yield categories, as measured during the CCEs: farmers with less than 10 quintals per acre (corresponding to severe damage), farmers with 10-16 quintals per acre (corresponding to moderate damage), and farmers with more than 16 quintals per acre (corresponding to no or minimal damage). Horizontal lines indicate the proportion of farmers receiving a payout, which is the main determinant of the variable costs associated with an insurance product. Note, however, that there were no severe covariate weather shocks affecting wheat during the one-year study period. Severe damage was instead due to other localized perils not covered by the WBI product, with almost four out of five cases of reported damage above 50 percent being due to hail storms and lodging of the wheat plant. This is an important factor to keep in mind when analyzing the performance of the WBI product.

**Figure 6. Payouts from different insurance products by crop-cutting yields**

First, when comparing PBI with WBI, the contrast is striking. As discussed, PBI correctly triggered for 71.4 percent of the 14 farmers with yields below 10 quintals per acre. The WBI product failed to trigger for these farmers because it was not designed to cover the hail storms and lodging events,
which damaged wheat over the season. For farmers with yields between 10 and 16 quintals per acre, WBI was more likely to trigger than the PBI product, making small insurance payouts to 36.4 percent of farmers. Worryingly, however, the WBI product triggered significantly more often than PBI for farmers whose crops were not or minimally damaged, issuing small payouts for 24.2 percent of farmers with yields above 16 quintals per acre. As a result, average yields are virtually indistinguishable for farmers without and with WBI payouts, implying a very large degree of overall upside basis risk in the WBI product. This is in line with the findings by Morsink et al. (2016), who report a very low degree of correlation between average yields and weather-index based insurance payouts across subdistricts in India. Nonetheless, the product may of course perform better during years with more extreme weather shocks.

The simulated AYI products also suffer from high levels of basis risk; the district-level product triggers payouts for, on average, 22.1 percent of the 14 farmers with severe damage (yields below 10 quintals per acre); 8.9 percent of the 33 farmers with moderate damage (yields of 10-16 quintals per acre); and 5.5 percent of the 310 farmers with no or minimal damage (yields above 16 quintals per acre). The cluster-level product (encompassing two nearby villages) performs slightly better, triggering payouts for 34.4 percent of farmers with severe damage, 13.1 percent of farmers with moderate damage, and 3.6 percent of farmers with no/minimal damage. As would be expected due to spatial correlation in yields, measuring yields for a cluster of nearby villages—although costlier and logistically more cumbersome—reduces basis risk compared to measuring yields at the district level. Still, both AYI products fail to trigger for most farmers with severe damage, and product performance varies widely across simulations, as indicated by wide confidence intervals.

PBI suffers from both advantages and disadvantages compared with the WBI product and the simulated AYI product. While PBI improves upon AYI by triggering significantly more often for farmers with severe damage, it does not help distinguish farmers with moderate damage from farmers with less or no damage. This indicates that, instead of testing PBI as a standalone product against potential alternatives, there is potential for it to complement existing index products, acting as a top-up component that can identify severe localized damage. Such a scheme also opens up the

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18 This result is of course only applicable to the specific WBI product implemented in this project. However, the product was carefully designed to reflect perceptions of both farmers and expert wheat agronomists in the study region.
possibility for the traditional index product to capture non-visible crop damage, a task for which PBI is not well suited. Indeed, the study followed this approach, by adding PBI coverage to a WBI product in order to both reduce basis risk of the WBI product and to cover non-visible wheat losses stemming from high-temperatures or non-seasonal rains. A similar scenario could be applicable to AYI products, where farmers could appeal to the AYI index not triggering when experiencing damage by sending in smartphone pictures taken from the ground under the PBI protocol.

Table 5 uses our data to illustrate the advantages of combining an AYI or WBI product with PBI. We first consider a lenient policy that triggers payouts when expert assessments indicate that the farmer experienced at least 20 percent damage. In Panel A, combining this lenient PBI policy with AYI reduces downside basis risk compared with the standalone AYI products in Figure 6, by increasing the proportion of farmers with less than 10 quintals per acre receiving payouts from less than 40 percent to approximately 75 percent. At the same time, it 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, it is worth noting that in identifying farmers with severe damage, the district-level product now performs as well as the product measuring yields at the village-cluster level, and the number of farmers with moderate damage that would receive payouts under the combined district-level product is almost as high as when AYI is offered at the village level. In other words, at a low additional cost, PBI reduces downside basis risk, potentially realizing cost savings by reducing the number of CCEs required for AYI loss indemnification.

Compared with introducing PBI in an AYI product, combining PBI with the WBI product results in a similar proportion of farmers with severe damage receiving payouts, while increasing the probability of payouts among farmers with moderate damage. However, under such a product, 30 percent of farmers without damage would receive payouts, due to the high degree of upside basis risk in the WBI product.

In Panel B, we consider bundling with a stricter PBI policy that pays out only in case experts identify more than 50 percent damage in the pictures. This product, when combined with AYI products, increases the overall proportion of farmers receiving payouts only slightly compared to the standalone AYI products in Figure 6, limiting the additional costs of providing PBI, while still significantly increasing the proportion of farmers with severe damage receiving payouts. The combined village-level product would have made payouts to 66.3 percent of farmers with severe damage.
damage, to 13.1 percent of farmers with moderate damage, and to only 3.9 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 in AYI products observed in the simulations, without significant increases in costs.

Table 5. Bundling PBI with index insurance products

| Probability of receiving a payout | Yields < 10 quintals/acre | Yields 10-16 quintals/acre | Yields > 16 quintals/acre | Overall proportion of payouts |
|----------------------------------|---------------------------|----------------------------|---------------------------|-------------------------------|
|                                  | Mean          | Std. dev. | Mean          | Std. dev. | Mean          | Std. dev. |                 |
| A. WBI/AYI + Lenient PBI        |               |          |               |          |               |          |                 |
| Weather index-based insurance (WBI) | 0.714 | 0.394 | 0.300 | 0.325 |
| Area-yield: District level       | 0.766 | 0.087 | 0.125 | 0.119 | 0.074 |
| Area-yield: Village cluster level | 0.744 | 0.035 | 0.179 | 0.101 | 0.167 |
| B. WBI/AYI + Strict PBI          |               |          |               |          |               |          |                 |
| Weather index-based insurance (WBI) | 0.571 | 0.364 | 0.248 | 0.271 |
| Area-yield: District level       | 0.657 | 0.143 | 0.089 | 0.136 | 0.060 | 0.082 |
| Area-yield: Village cluster level | 0.663 | 0.069 | 0.131 | 0.052 | 0.039 | 0.017 |
| Number of observations in total** | 14 | 33 | 310 | 357 |
| Number of weather stations       | 5 | 17 | 25 | 25 |
| Number of districts              | 2 | 6 | 6 | 6 |

Notes: * Cost estimates between standalone AYI and PBI are not comparable since they depend on statistical estimation of expected payouts under each insurance system, for which we do not count with data. Instead, the cost estimates under PBI reflect the additional costs for, respectively, loss assessments and additional expected payouts for idiosyncratic events (for which we take as representative Rabi 2016-17 season payouts). Mean and standard deviation based on a 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.

It is also worth noting here that although small, and hence omitted from the analyses above, the costs of loss assessment under PBI versus either WBI and AYI are of a different nature. On one hand, WBI and AYI products have a fixed implementation cost at the cluster level, introducing an implicit tradeoff between cost reduction and basis risk: while a geographically narrowly-defined index may reduce the level of basis risk, it can do so only at the expense of increasing the per-cluster implementation cost compared with products that use a sparser network of weather stations or conduct a smaller number of CCEs. Such a tradeoff is not present in PBI, where the quality of coverage of the insurance product is unaffected by increasing cluster size. Nevertheless, using pictures as a method for loss verification carries a constant variable cost (in terms of the time
needed for experts to assess losses for each individual site). This suggests that PBI may lend itself well to high-risk cash crops that are not grown on a sufficiently large scale to justify CCEs.

All in all, the exercise above indicates that the main cost of implementing PBI in the context of an existing insurance scheme—the costs associated with additional payouts—are paired with significant improvements in insurance coverage for farmers experiencing severe damage. The basis-risk reducing benefits of PBI may well compensate for the additional costs. With time, once algorithms for automatic loss assessment are developed and tested—thus lowering the variable costs of PBI—the case for PBI would be even stronger. Of course, PBI shifts a fraction of the burden to the farmer, in terms of the time spent in taking repeat pictures and the cellular data costs from uploading these pictures to the server. This may be an argument towards overcoming the additional burden on the farmer through subsidizing PBI premiums by, for instance, including it within the umbrella of a national crop insurance scheme (the PMFBY in the case of India).

5. Conclusions

Picture-Based Insurance (PBI) is a new approach to improve smallholder farmers’ access to affordable but high-quality crop insurance. By leveraging increasing smartphone ownership among smallholder farmers and relying on automated image processing techniques, the goal of PBI is to combine key advantages of index insurance—fast and inexpensive claims processing—with those of indemnity insurance—low basis risk and easy-to-understand products. To our best knowledge, the feasibility of this approach has never been evaluated systematically, and this study is a first step in that direction. We find that (a) farmers are able—at large—to follow picture-taking protocols; (b) agronomists and farmers agree that the most important risks in wheat production can be visible in pictures, and experts are able to detect such damage in the pictures; and (c) picture-based insurance can provide payouts that are better correlated with actual yield losses than those from weather index-based insurance and seems to offer considerable advantages to other common index products such as satellite-based or area-yield-based insurance.

In related research, we study PBI sustainability considerations such as the extent of moral hazard observed during this first season and its dynamics over time, including product design aspects that can help to limit this moral hazard issue (Ceballos and Kramer, 2018a); analyze differences in willingness to pay for picture-based insurance versus weather index-based insurance; and test to
what extent there is adverse selection and how to overcome it (Ceballos and Kramer, 2018b). These
studies find limited adverse selection and moral hazard during the feasibility study, while PBI
could increase demand compared with WBI products. Related research analyzes whether image
processing algorithms could be developed to automate loss assessment and finds that greenness
indices extracted from the smartphone imagery can be used to approximate crop growth stage with
greater accuracy than vegetation indices derived from satellite imagery (Hufkens et al., 2019).

Moving forward, scaling-up of the PBI approach could take a few forms. First, an insurance
product could be implemented featuring two layers: (i) a standard low-cost index, for instance a
weather index or a coarse area-yield index; and (ii) damage estimates from visual inspection of
pictures by experts. To make this approach scalable, the main difference with the approach
followed during the first season would be for time lapses of pictures to be assessed only in case
the first layer does not trigger a significant payout, and only for farmers who report experiencing
visible damage that can be verified from the smartphone pictures. As a way to align reporting
incentives, a no-claims discount for the purchase of the product in future seasons could be used to
prevent farmers from reporting false claims. This approach is already feasible at a moderate scale.
The labor cost of picture-based loss assessments in a reasonable time window is only about Rs.
21.9 per claim, or 0.17% of the sum insured in our pilot products, making this mechanism
affordable at scale (e.g. schemes with up to 50,000 acres insured).

Second, combining ground pictures and claims data from the initial seasons, together with weather
data, georeferenced yield data, and satellite observations of insured plots, machine learning
algorithms can be trained for automated claims processing, which would decrease cost and
improve the speed of damage assessments even further. For instance, vegetation and texture
indices are already being derived from the pictures throughout the season (c.f. the PhenoCam
project, see Hufkens et al., 2016 and Richardson et al., 2017), relying on algorithms that can detect
the line of horizon and determine a region of interest with visible crop in a given individual
picture.19 While the development of machine learning algorithms requires a large amount of data
to train reliable models, it would indeed be possible to count with functional models after a few

19 Pictures could also be used for estimating crop growth stages in near-real time, for purposes of geographic crop
development monitoring and yield forecasting, or for refining weather index-based products by dynamically adjusting
triggers according to the particular growth stage a crop is in. See Dalhaus et al. (2018) for an example of the latter
approach.
seasons, which would boost the scalability of the PBI approach, whether in combination with other index products or as a standalone instrument.

Third, although farmers are able and willing to take enough pictures for loss assessments, there is room for improvement. In this initial implementation, communication was one-way: from the farmer to the project. Future efforts could make communication two-way, potentially in partnership with telecoms or financial institutions trying to increase their market share among smallholder farmers and concentrate on bundling PBI with picture-based agro-advisory and pest detection services to make the process more inclusive and make the benefits of taking pictures more salient to farmers. This type of bundling could also help minimize any potential picture tampering as it would be in the best interest of the farmer to provide the most accurate information on the crop status. Such a holistic risk management system could provide additional benefits to farmers and greatly improve the sustainability and scalability of the PBI approach.

Importantly, this approach is not exclusively reserved to areas with sufficient smartphone penetration. An equivalent insurance model could be achieved by relying on village representatives, who could be provided with an inexpensive Android smartphone (when one is not already available) and requested to visit every insured plot a few times a week to capture the corresponding repeat picture. This representative could also serve as distribution channel and as a key link with the insurance company, in exchange for a commission on premiums.

In conclusion, smallholder farmers can benefit from an ecosystem of insurance products available to them, that can cater to their individual preferences and characteristics and that can best tackle the nature of production risks in a given geographic area and for a given crop. In this regard, PBI is a promising concept to complement existing insurance products, serving as an additional layer to protect against extreme damage and reduce basis risk, while at the same time retaining some of the cost advantages of more traditional index schemes. Such an approach has the potential to bring about important changes in the way that insurance is offered to smallholders in rural areas of the developing world.
References

Barrett, C., and J. McPeak, 2006. “Poverty Traps and Safety Nets.” In Poverty, Inequality and Development: Essays in Honor of Erik Thorbecke, edited by A. de Janvry and R. Kanbur, 131–154. New York: Springer.

Berhane, G., S. Dercon, R.V. Hill, and A. Taffesse. 2015. “Formal and Informal Insurance: Experimental Evidence from Ethiopia.” Paper presented at International Conference of Agricultural Economists, Milan, August 8–14.

Bhushan, C., and V. Kumar, 2017. “Pradhan Mantri Fasal Bima Yojana: An Assessment.” Centre for Science and Environment, New Delhi.

Cai, J., 2013. “The Impact of Insurance Provision on Households’ Production and Financial Decisions,” MPRA Paper 46864, University Library of Munich, Germany.

Cai, H., Y. Chen, H. Fang, L. Zhou, 2009. “Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment,” NBER Working Papers 15396.

Carter, M.R., C.B. Barrett, S. Boucher, S. Chantarat, F. Galarza, J.G. McPeak, A.G. Mude, and C. Trivelli, 2008. “Insuring the Never Before Insured: Explaining Index Insurance through Financial Education Games.” BASIS Briefs, University of Wisconsin, Madison.

Carter, M.R., Cheng, L. and Sarris, A., 2016. “Where and How Index Insurance Can Boost the Adoption of Improved Agricultural Technologies.” Journal of Development Economics 118(1): 59-71.

Ceballos, F. and B. Kramer, 2018a. “Big Brother Might be Watching You: Testing for Moral Hazard in Picture-Based Crop Insurance.” Mimeo.

Ceballos, F. and B. Kramer, 2018b. “How Attractive is Picture-Based Insurance? Willingness to Pay and Testing for Adverse Selection.” Mimeo.

Chantarat, S., A.G. Mude, C.B. Barrett, and M.R. Carter, 2013. “Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya.” Journal of Risk and Insurance 80(1): 205-237.
Cole, S.A., X. Giné, J. Tobacman, P.B. Topalova, R.M. Townsend, and J.I. Vickery, 2013. “Barriers to Household Risk Management: Evidence from India.” *American Economic Journal: Applied Economics* 5 (1): 104–135.

Cole, S.A., X. Giné, J.I. Vickery, 2017. “How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment.” *The Review of Financial Studies* 30(6): 1935–1970.

Dalhaus, T., O. Musshoff, and R. Finger, 2018. “Phenology Information Contributes to Reduce Temporal Basis Risk in Agricultural Weather Index Insurance.” *Scientific reports* 8(46): 1–10.

de Janvry, A., V. Dequiedt, and E. Sadoulet. 2014. “The Demand for Insurance against Common Shocks.” *Journal of Development Economics* 106: 227–238

Dercon, S., R.V. Hill, D. Clarke, I. Outes-Leon, and A. S. Taffesse. 2014. “Offering Rainfall Insurance to Informal Insurance Groups: Evidence from a Field Experiment in Ethiopia.” *Journal of Development Economics* 106: 132–143.

Dercon, S., and J. Hoddinott, 2004. “Health, Shocks, and Poverty Persistence.” In *Insurance against Poverty*, edited by S. Dercon, 123–136. Oxford, UK: Oxford University Press;

Flatnes, J.E., and M.R. Carter, 2015. “Fail-Safe Index Insurance without the Cost: A Satellite Based Conditional Audit Approach,” Mimeo.

Hazell, P., C. Pomareda, and A. Valdes. 1986. *Crop Insurance for Agricultural Development: Issues and Experience*. Baltimore: Johns Hopkins University Press.

Hill, R.V., L.M. Robles, and F. Ceballos. 2016. “Demand for a Simple Weather Insurance Product in India: Theory and Evidence.” *American Journal of Agricultural Economics* 98 (4): 1250–1270.

Hufkens, K., E.K. Melaas, M.L. Mann, T. Foster, F. Ceballos, M. Robles, and B. Kramer, 2019. “Monitoring crop phenology using a smartphone based near-surface remote sensing approach,” *Agricultural and Forest Meteorology* 265: 327-337.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry, 2014. “Agricultural Decisions after Relaxing Credit and Risk Constraints.” *The Quarterly Journal of Economics* 129(2): 597-652.
Lobell, D.B., G. Azzari, M. Burke, S. Gourlay, Z. Jin, T. Kilic, and S. Murray, 2018. “Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis in Uganda.” World Bank Policy Research Working Paper No. 8374.

Morsink, K., D. Clarke, and S. Mapfumo, 2016. “How to Measure whether Index Insurance Provides Reliable Protection.” World Bank Policy Research Working Paper No. 7744.

Matul, M., A. Dalal, O. De Bock, and W. Gelade. 2013. “Why People Do Not Buy Microinsurance and What We Can Do about It.” Briefing Note 17. Geneva: Microinsurance Innovation Facility.

Mobarak, A.M., and M. Rosenzweig, 2012. “Selling Formal Insurance to the Informally Insured.” Working Paper No. 97, Economic Growth Center Discussion Paper No. 1007, Yale University.

Porter, J. R., Xie, L., Challinor, A., Cochrane, K., Howden, S., Iqbal, M., Lobell, D., Travasso, M., Netra Chhetri, N., Garrett, K., 2014. “Food security and food production systems.” In: Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea, M. D., et al. (Eds.), “Climate Change 2014: Impacts, Adaptation, and Vulnerability. Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.” Chapter 7, pp. 485–533.

Richardson, A.D., K. Hufkens, T. Milliman, D.M. Aubrecht, M. Chen, J.M. Gray, M.R. Johnston, T.F. Keenan, S.T. Klosterman, M. Kosmala, E.K. Melaas, M.A. Friedl, and S. Frolking, 2017. “Tracking Vegetation Phenology across Diverse North American Biomes using PhenoCam Imagery.” Scientific Data.

Stanimirova, R., H. Greatrex, R. Diro, G. McCarney, J. Sharoff, B. Mann, A.L. D’Agostino, M. Rogers-Martinez, S. Blakeley, C. Small, and P. Ceccato, 2013. “Using Satellites to Make Index Insurance Scalable.” Final IRI Report to the ILO Micro-Insurance Innovation Facility.
Appendix Figure A1. Farmers’ concern about and last season occurrence rate of hazards

Note: The figure presents the extent to which farmers are concerned about different hazards (self-reported at baseline) and the average rate of occurrence of the hazard during the Rabi 2016/17 (self-reported at endline). To measure the former, we asked farmers during the baseline to divide tokens between different hazards, with more tokens being allocated to hazards that worried the farmer more.
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