INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

IFPRI Discussion Paper 02088

December 2021

The Role of Asymmetric Information in Multi-Peril Picture-Based Crop Insurance

Field Experiments in India

Francisco Ceballos

Berber Kramer

Markets, Trade, and Institutions Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Francisco Cebbalos (f.ceballos@cgiar.org) is a Research Fellow in the Markets, Trade, and Institutions Division at the International Food Policy Research Institute (IFPRI), Washington, DC.

Berber Kramer (b.kramer@cgiar.org) is a Senior Research Fellow in IFPRI's Markets, Trade, and Institutions Division, Washington, DC.

Notices

[1]IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by IFPRI.

[2] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

Abstract

Smallholder farmers in developing countries generally lack access to affordable agricultural insurance, in part because of high loss verification costs and asymmetric information in indemnity insurance and basis risk in index-based insurance. Advances in remote sensing and other digital technologies can help overcome these challenges by allowing for low-cost, remote loss verification, and settling claims based on observed visible damage in a farmer's fields. By effectively proxying for indemnity insurance, however, such a product may be subject to moral hazard and adverse selection. We test these hypotheses leveraging the rollout of picture-based crop insurance among smallholder farmers in northwestern India. We find no evidence of moral hazard or adverse selection, and that the use of technologies increases willingness to pay. We conclude that digital technologies are a valuable tool to provide low cost, sustainable crop insurance remotely, at lower levels of basis risk than index products.

Keywords: risk and insurance; mobile technology; digital insurance; moral hazard; adverse selection

Acknowledgements

We gratefully acknowledge Braulio Britos, Amandeep Chhabra, and Matthew Krupoff for excellent research assistance; Azad Mishra and Siddhesh Karekar from HDFC for pioneering the implementation of PBI; and the Borlaug Institute for South Asia for their dedication to data collection. We received valuable suggestions from Chris Barrett, Glenn Harrison, Dean Karlan, Craig Mcintosh, Chris Udry, as well as seminar participants at Göttingen University, ZEF Bonn, and numerous conferences and workshops organized by (among others) the International Fund for Agriculture and Development (IFAD), Innovation for Poverty Action (IPA), Georgia State University's Center for the Economic Analysis of Risk (CEAR), M.S. Swaminathan Research Foundation, Madras School of Economics, and the International Labor Organization (ILO). This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). Funding support for this study was provided by PIM and the International Initiative for Impact Evaluation (3ie). This paper has not gone through IFPRI's standard peer review procedure. The opinions expressed here belong to the authors, and do not necessarily reflect those of PIM, 3ie, IFPRI, or CGIAR.

1. Introduction

Billions of rural households worldwide depend on agricultural incomes for subsistence. Yet, agriculture is among the riskiest economic activities. Weather occurrences and other natural hazards such as pests and diseases can induce large losses to crops, disproportionately affecting poor farming households' future through reduced food consumption or schooling (Dercon and Hoddinott, 2004; Barrett and McPeak, 2006). Moreover, large disruptive effects of extreme weather events on production may be subsequently transmitted to other layers of the agricultural value chain (e.g., traders, wholesalers, processors, suppliers) and to rural financial markets (through loan defaults, illiquidity). To reduce their exposure to these risks, farmers tend to diversify their livelihoods by investing in low-risk yet low-return activities, impeding them from capturing the full range of benefits from specialization, and holding back investment into riskier opportunities with a higher expected income, causing an efficiency loss.[1]

Formal insurance is a natural solution to some of these problems, but agricultural insurance penetration in rural areas of developing countries has been historically very low. Indemnity insurance, which requires on-site loss verification by a specialized adjuster, is expensive to provide for smallholder farmers in remote areas and subject to information-asymmetry problems such as moral hazard or adverse selection, further increasing premiums (Hazell, Pomareda, and Valdes, 1986). In contrast, index insurance, which compensates the farmer according to the value of an objectively measured proxy for losses (the 'index'), offers a promising alternative as index-based claims settlement is faster and less expensive than on-site indemnification. Moreover, since payouts do not depend on an individual farmer's riskiness or actions, there is no asymmetric information. However, demand for index-based insurance has been low due to basis risk, which is the risk that an index does not adequately capture crop damage at individual plots, along with farmers' lack of trust and understanding of index insurance (Cole *et al.*, 2013; Matul *et al.*, 2013).

In this context, digital technologies have the power to disrupt agricultural insurance systems, including their design, distribution, loss verification, and claims settlement. For instance, technologies such as digital know-your-customer protocols and ID verification, mobile money

[1] Although rural households can resort to informal risk coping strategies such as holding savings or semi-liquid assets that can be easily sold in times of need, borrowing from informal sources, and relying on gifts from social or family networks, these strategies are costly, and have limited potential to mitigate risks, in particular in the event of the covariate risks that are common to agriculture (Townsend, 1994).

networks, blockchain and smart contracts can simplify and expedite insurance enrollment, distribution, and claims settlement, lowering transaction costs and allowing for more affordable insurance products that would otherwise not be feasible through in-person agent models. The increased availability of sensors and inexpensive weather stations can reduce basis risk of weather-index insurance products; drones and satellites can bring down the cost and increase the precision of area-yield index insurance; and by enabling field-specific loss assessment remotely, cellphone pictures, drones, and micro-satellites can increase the affordability of traditional indemnity insurance models, where farmers are compensated for the actual losses they incurred. Such increase in precision, however, may re-introduce the risk of information asymmetry issues such as moral hazard and adverse selection, potentially undermining the sustainability of said approaches.

This paper provides empirical evidence of the extent to which these types of innovations are associated to the presence of moral hazard and adverse selection in insurance, leveraging data collected during an initial rollout of picture-based crop insurance (PBI) in the states of Haryana and Punjab, India. PBI relies on a stream of plot-level smartphone pictures of insured crops, taken by farmers from sowing to harvest, to document crop damage and pre-damage growth and management of insured crops. Because it does not rely on an index, PBI represents a new form of indemnity insurance where losses are assessed remotely through pictures instead of in-person visits, minimizing the costs of loss verification. This raises the following questions: (1) Do farmers strategically reduce crop management efforts (moral hazard) or actively induce damage or tamper with pictures (insurance fraud) to receive payouts under PBI? (2) To what extent do riskier farmers self-select into PBI insurance or selectively enroll plots that are more prone to damage? In other words, is PBI prone to adverse selection?

To test for the presence of moral hazard, we rely on the study's randomized design, where half of the 100 villages were offered weather-based index insurance (WBI) alone and the other half an additional coverage from PBI. This design allows us to test whether farmers in the PBI treatment arm applied lower quantities of inputs (including labor), suffered higher levels of damage, or obtained lower average yields than their counterparts in the WBI only treatment arm. We test these through survey data collected before and after the season, independent expert loss assessments based on the stream of pictures for each farmer's plot, and objective yields from crop cutting experiments conducted right before harvest among a subset of farmers. We find no evidence of reduced input use or yields, or higher damage among farmers with PBI coverage, indicating that moral hazard or insurance fraud did not seem to play a role during this initial season.

Next, we test for adverse selection through positive correlation tests (Chiappori and Salanié, 2000), relying on two separate identification strategies. First, we rely on a field experiment conducted among a subsample of 100 farmers who had participated in the formative evaluation, that elicited incentivized measures of their willingness to pay (WTP) for a set of index-based and PBI products through a Becker-Degroot-Marschak (BDM) auction mechanism. We correlate a respondent's valuation of PBI coverage with indicators that proxy for the farmer's risk of experiencing crop damage, and thus of receiving insurance payouts, including measures of past damage and yields. In the presence of adverse selection, farmers with higher risk should have a higher valuation of PBI, resulting in a positive correlation.

Second, we test whether farmers, in choosing which of their different plots to enroll, select a plot with an increased probability of crop damage, due to for instance poor irrigation access or soil quality. We measure these characteristics prior to WTP elicitation and subsequent insurance coverage, so that our estimate of adverse selection is unbiased by moral hazard or treatment effects.[2] To our surprise, we find no evidence of adverse selection in our sample, regardless of whether we use the first or the second identification strategy. We discuss alternative interpretations of these results in the concluding section.

This paper relates to two strands of the literature. First, our paper relates to studies analyzing the extent of moral hazard in crop insurance markets. For instance, some authors report evidence of lower input use among insured farmers (Smith and Goodwin, 1996), while others find increased claims or indemnity payments (Rao and Zhang, 2020;Wu , Goodwin, and Coble, 2020; Coble et al., 1997). In contrast, Horowitz and Lichtenberg (1993) find increased chemical input use among insured farmers and interpret this as indicative of moral hazard inducing farmers to invest in higher risk production methods. Most of these papers, however, are based on data from the U.S. agricultural program and, as such, involve farmers quite different from those in our setting. In

[2] If households are offered different insurance premiums, and the variation in the insurance premium is exogenous, an alternative approach to circumvent such biases is to use a price test, in which claims data are compared between households enrolling at a high premium and households enrolling at a low premium to obtain a monetary measure of adverse selection (Polimeni and Levine, 2012). Akerlof (1970) shows that in the presence of adverse selection, the high-premium sample will have higher claims than the low-premium sample, and the difference in claims will reflect the cost of adverse selection. We will apply this method in future research.

addition, none of the above studies provide experimental evidence on moral hazard based on random treatment assignment. Contrary to most of this literature, our paper does not find differential input use (either positive or negative) nor differential damage or yields between farmers in both treatment arms.

Second, we relate to the literature on adverse selection. Adverse selection is considered a threat to the sustainability of multi-peril crop insurance, since higher enrollment of those who are more prone to damage would raise insurance premiums, crowding out demand from lower-risk and poorer farmers, jeopardizing impacts. Theory, however, suggests that selection into insurance is not necessarily adverse, as individuals will also select based on characteristics associated with precautionary behaviors and lower risks. Several studies find that not only high-risk individuals but also individuals who take precautionary and risk-reducing actions are more likely to enroll in insurance, and such advantageous selection often offsets any adverse selection (De Meza and Webb, 2001; Finkelstein and McGarry, 2006; Doiron, Jones, and Savage, 2008; He *et al.*, 2018). Our finding of zero selection on risk characteristics is consistent with this literature, and with findings that there cannot be adverse selection if there is low demand (Banerjee, Duflo, and Hornbeck, 2014).[3]

Finally, these findings improve our understanding of behavior in the roll-out of technology innovations in financial instruments such as savings, credit, digital payment mechanisms and insurance. Whilst digital innovations are often seen as a major driver of financial inclusion (e.g., Suri and Jack, 2016), other studies are painting a more cautious picture about the potential coverage and impacts of digital finance (Benami et al., 2021; Parlasca et al., 2022). A previous paper focused on the feasibility of PBI (Ceballos, Kramer, and Robles, 2019) found that farmers are able and willing to take regular pictures of their fields, that severe crop damage is visible and quantifiable through a stream of such pictures, and that picture-based loss assessment can identify damage more accurately than a weather index-based insurance product, considerably reducing basis risk. However, because PBI compensates farmers according to visible losses in their fields, traditional information asymmetry issues that affect other indemnity insurance markets could hurt PBI's sustainability. This paper shows that in its initial rollout, such issues did not turn out to be a

[3] Cohen and Siegelman (2010) provide an overview of the literature testing for adverse selection in insurance markets. Several studies have empirically tested for adverse selection in crop insurance, including He *et al.* (2017), Jensen, Mude and Barrett (2018), Just, Calvin and Quiggin (1999), and Makki and Somwaru (2001).

concern, yet demand challenges remain. As such, we argue that the priority should be to embrace the use of digital innovations to strengthen the design of agricultural insurance instruments, identifying their place within a broader ecosystem of risk management instruments, polishing the rough edges, and cultivating demand, rather than getting such young innovations paralyzed by concerns around moral hazard and adverse selection.

The remainder of this paper proceeds as follows. Section 2 discusses the project's context while Section 3 presents the data sources used and the estimation methodologies. Section 4 tests the moral hazard and adverse selection hypotheses. Section 5 concludes.

2. Context

The study was conducted in several districts within the states of Haryana and Punjab, located in northwest India, around the initial roll-out of a picture-based crop insurance (PBI) initiative. Crop insurance in India has a long and complex history (see Cariappa, Lokesh, and Ramesh, 2017 and references therein for an overview). PBI was introduced first during the Rabi 2016/17 (winter) season by the International Food Policy Research Institute (IFPRI), Borlaug Institute for South Asia (BISA), and HDFC Ergo General Insurance, Ltd., to identify solutions to strengthen the nationwide government-sponsored crop insurance scheme, called Pradhan Mantri Fasal Bima Yojana (PMFBY). The PMFBY was launched by the Government of India starting in the 2016 Kharif (monsoon) season, building on earlier weather index-based and area yield index-based crop insurance schemes.

The PMFBY expanded subsidized multi-peril crop insurance with mandatory coverage for farmers taking an agricultural loan from an official credit institution. The scheme is heavily subsidized, with the farmer having to pay a maximum premium of 2 percent of the sum insured for Kharif crops, 1.5 percent for Rabi crops, and 5 percent for annual commercial and horticultural crops. Claims settlement occurs through several mechanisms, but mainly through an area-yield index-based approach, which triggers payouts when average yields within a cluster of villages (measured through state-operated crop cutting experiments) fall below a historical threshold. The scheme also has an indemnity-based component, providing coverage for prevented sowing, mid-season adversities caused by covariate weather shocks, localized calamities such as flooding, hailstorms and landslides, and post-harvest losses due to perils such as excess rainfall. Thus far, however, payouts have been mainly triggered based on the area-yield index.

To implement this area-yield index, states need to randomly select, at the time of the harvest, at least four sites per Gram Panchayat (a cluster of villages) to measure yields for every crop that is covered through the PMFBY. This is a daunting operation, and challenges in the monitoring and implementation of the crop cutting experiments (CCEs) have led to disputes and delays in claims settlement. Recognizing this, the PMFBY has provisions for the use of innovative technology throughout the insurance process, from enrollment to claims settlement. This includes testing: the use of smartphone pictures to capture and upload data of CCEs; the use of satellite imagery to reduce sampling biases; and the use of drones and other remote sensing technologies to provide coverage for prevented sowing, mid-season adversities, localized calamities, and post-harvest losses. Remote sensing applications face a number of challenges, including cloud cover during the main production season, multi-cropping and small plot sizes, and a need for ground truth data, which ground pictures can provide; while drone applications are limited by short battery life (constraining geographic coverage), require considerable data processing power and storage space, and are subject to numerous regulatory challenges (Benami et al., 2021). In this context, PBI stands as a promising digital technology to support existing PMFBY activities.

The study targeted 750 wheat farmers from 50 villages in six districts in Haryana and Punjab, where wheat is the main crop grown during the winter season.[4] We selected three districts in Punjab and three in Haryana for which HDFC Ergo could source rainfall and temperature data from weather stations, to allow for comparisons of the performance of PBI and weather index-based insurance. Twenty-five weather stations were selected from a list of available ones, stratified by district, with the number of weather stations per district (ranging from three to eight) being proportional to district size. Subsequently, two rural villages were randomly selected 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). This resulted in a study sample of 50 villages.

Within every village, 15 farmers were invited to participate in the project, for a total of 750 invited farmers. These farmers were randomly selected from a list of all farmers within the village

[4] Given that irrigation is widespread, drought is not considered a major risk to wheat, but instead, major risks include excess rainfall, hail, extreme heat, and pests and diseases. In Haryana, PMFBY coverage for major crops including wheat is available, whereas Punjab has decided not to join the scheme, and relies on ex-post disaster relief and loan waivers for natural calamities instead.

who satisfied the following criteria: (1) having less than 15 acres of operational farmland and (2) planning to grow at least two acres of wheat during the upcoming Rabi (winter) season. They were informed that they would receive an insurance product free of charge for one acre of wheat, subject to sending in pictures of that plot on a regular basis, following a picture-taking protocol designed to be scalable whilst also minimizing incentives for moral hazard or potential tampering with pictures. Farmer outreach and recruitment were conducted by a team of trained enumerators.

Pictures were to be taken through a smartphone app, KisanCam, especially introduced as part of the project. To enroll, farmers took an initial overview picture of their plot, facing north. Farmers were asked to take three repeat pictures per week throughout the entire season, taken from the exact same location and with the same view angle as the initial picture. To facilitate this, the smartphone app included geo-tags and visual aids in the form of a "ghost" image (a partially transparent image of the initial picture) that allowed the farmer to align static features in the landscape (such as distant trees or structures) with those in the initial picture. The field team provided technical support to farmers throughout the season. Valid pictures were uploaded to an online server and processed by the research team. Importantly, loss assessment relied on the time lapse of overview pictures instead of on snapshots zoomed in on damaged crops because the latter approach would be more susceptible to tampering.

At the end of the study season, an independent panel of wheat experts inspected the time lapse of pictures and determined whether there had been any damage to the crop. When damage was determined to be above 20 percent, a payout was triggered and deposited in the farmer's bank account directly by HDFC, the insurance company. Findings from the initial season speak to PBI's practical feasibility. Farmers were overall willing and able to provide regular pictures of their fields and independent agricultural experts were able to identify damage and initiate insurance claims directly from the evidence available in the stream of pictures from a given site, particularly in cases of severe damage (Ceballos, Kramer, and Robles, 2019).

Column 1 in Table 1 shows average characteristics for the final sample of 736 participating households that completed a baseline survey (described below). The average farmer 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 households 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 respondents are used to taking pictures with their smartphones and report having regular network signal in their plots.

3. Data and methods

In order to assess the presence and extent of problems arising from information asymmetries in PBI, we conduct two separate sets of analyses. To evaluate moral hazard, we rely on survey data and high-frequency data collected through the smartphone application on input use, damage, and yields, leveraging experimental between-subject variation in whether a farmer had PBI coverage. To evaluate adverse selection, we rely on experimental willingness to pay data elicited among a sub-sample of farmers and survey data on plot characteristics at baseline. We describe these experiments and the data collection activities, together with other data sources, next.

3.1. Testing for moral hazard

To create experimental between-subject variation in whether a farmer had PBI coverage, participating villages were randomly assigned to one of two treatment arms:

- WBI + pictures: In these villages, farmers taking crop pictures regularly received weather index-based insurance (WBI), providing coverage against excess rainfall and above-normal temperatures (the control group);
- WBI + PBI: In these villages, farmers taking crop pictures regularly received the same WBI product plus picture-based insurance (PBI) coverage, offering a payout when damage was visible in pictures of insured crops.

Prior to the roll-out of the intervention, in July 2016, an in-person baseline survey was conducted with all farmers invited to participate, yielding 736 baseline interviews. The survey collected an array of information on farm and household characteristics, including data on plots and plot-level characteristics, adoption of agricultural technologies, cultivation practices, input use, income, risk attitudes and perceptions, past instances of damage, and experiences with insurance. In May-June 2017, after the Rabi season was over, an endline survey was conducted among all farmers who had participated in the baseline survey, though only 690 of them were reached, for an overall attrition rate of 6.25%. The endline survey gathered further data on cultivation practices over the Rabi 2016/17 season, including input use and self-reported wheat output.

In addition to self-reported survey data, our moral hazard analyses rely on objectively measured yields, damage assessments from experts, and high-frequency input use data. Objective wheat yields were measured through project-led CCEs just prior to harvest.[5] All in all, we collected CCE data from 437 farmers, mostly due to the fact that some farmers had already harvested before the team reached a village or that the crop had not yet ripened at that time. Damage assessments were provided by independent experts for each site at the end of the Rabi 2016/17 season, in terms of both damage not due to and due to mismanagement by the farmer (as determined by the experts themselves). Since three experts assessed each of the sites, we construct the median assessment across all experts for the insured site of each farmer. Although these assessments were used to determine insurance payouts for farmers with PBI coverage, experts also reviewed pictures from farmers with the WBI + pictures product (without knowing the type of coverage to which the farmer had been assigned). Loss assessments were conducted for the 467 farmers who qualified for insurance by actively taking pictures (at least two throughout the season). We find no evidence of attrition bias in terms of observable farm and household characteristics in either the CCE or loss assessment subsamples (see Ceballos, Kramer, and Robles, 2019, for details).

Table 1 shows average baseline farmer characteristics across the two treatment arms. Columns 7 and 8particularly present the probability that baseline characteristics differ across the two samples, clustering standard errors at the village level. Overall, the random assignment of treatment worked quite well in terms of observables, with the majority of baseline characteristics being balanced across treatment arms. The only exceptions are total area of a farmer's plots, with farmers in the control group declaring roughly half an acre less than those in the treatment group, and whether the farmer practices zero tillage with a Happy Seeder machine, with farmers in the control group slightly more likely to do so. In order to be conservative, these characteristics will be used as control variables in our analysis.

We test for moral hazard by relying on the randomized assignment of farmers to treatment (WBI + PBI) and control (WBI + pictures). In the presence of moral hazard, we would expect farmers offered PBI coverage to show reduced input use (fertilizers, pesticides, herbicides and

[5] The field team informed farmers of the CCEs only the day before their visit, so that farmers would not adjust their behavior in anticipation of these validation visits for picture-based loss assessments.

fungicides, and farm labor), lower yields, or more severe crop damage. To test for this, we follow an intent-to-treat (ITT) post estimation via ordinary least squares (OLS) as follows

$$Y_{vi} = \alpha + \beta T_v + \gamma Z_{vi} + \epsilon_{vi} \quad [1]$$

where Y_{vi} represents an outcome (i.e., input use, yields, or damage) for farmer i in village v, T_v is a treatment dummy taking the value of 1 if village v was assigned to the PBI treatment and 0 otherwise, and Z_{vi} is a vector of farmer-specific controls unbalanced in the random treatment assignment (total acreage and ownership of happy seeder). In addition, we conduct an ANCOVA estimation as follows

$$Y_{vi} = \alpha + \beta T_v + Y_{vi,BL} + \gamma Z_{vi} + \epsilon_{vi} \quad [2]$$

by including the baseline value of the outcome variable as an additional regressor. By absorbing some of the individual variation in input use, damage, and yields, such a specification improves power (McKenzie, 2012). In all specifications, we include weather stations fixed effects, which corresponds to the level of village randomization. In addition, we cluster standard errors at the village level.

3.2. Testing for adverse selection

The analyses on adverse selection, in turn, rely on data of farmers' willingness to pay for insurance products collected through experimental auctions after the Rabi 2016/17 season and on plot characteristics captured during the baseline survey.

Willingness to pay was elicited in July 2017 as a follow-up to the first season of implementation and data collection. The WTP elicitation involved experimental auctions with a subsample of 100 farmers in 20 villages, from those that had participated in the initial season. To ensure familiarity with the picture-taking protocol, only villages with at least seven participating farmers (who had taken at least one repeat picture during the season) were considered. Amongst these villages, we selected those villages with the highest levels of engagement (as measured by the total number of pictures taken in that village). Finally, within each village, we ranked the top seven farmers in terms of their engagement in the first season. To reward active participation, the top five were invited to participate in the study, whereas the other two farmers served as replacements.

For each participant in the experiment, we elicited WTP for four different products:

- **WBI only**: offering coverage against excess rainfall and above-normal temperatures, without having to take pictures of the crop.
- **WBI + pictures**: identical to the *WBI only* product but paying out conditional on the farmer taking pictures of the crop regularly.
- **WBI + PBI**: identical to the *WBI + pictures* product but providing additional coverage against damage visible in the pictures.
- **PBI only**: identical to the *WBI + PBI* product but excluding coverage against excess rainfall and above-normal temperatures that is not visible in the pictures.

WTP was elicited through an incentivized, adjusted Becker, Degroot, and Marschak (1964) method (henceforth, BDM). The exercise proceeded as follows. The participant was requested to write down his/her maximum WTP for each of the products in four spaces of a randomly picked scratch card (Figure 1). By scratching the ink off, the card revealed a random product and a random premium offer. If a participant's WTP for the selected product was at or above the premium offer, s/he would be required to purchase the product at that special premium (and not at his/her full WTP). Otherwise, the participant would not receive that product and would not be able to purchase any insurance at that point in time. The entire procedure was explained in advance and a practice session—with a real practice card—was conducted before the real session took place. All sessions were conducted in the local language, either in Hindi or in Punjabi.

The BDM method has been extensively used in the WTP literature (Bageant and Barrett, 2017; Cole, Giné and Vickery, 2017; Cole, Stein and Tobacman, 2011; Stein and Tobacman, 2016) because it incentivizes respondents to reveal their true maximum WTP. Writing down a lower amount could result in being unable to buy the product for a price at which the respondent would like to buy it. Vice versa, stating a higher amount could result in having to buy the product at too high of a price. Since the participant knows in advance that the random price is already printed under the scratch-off ink, this application of the BDM method avoids one of the common objections against it: that a participant may not reveal his true valuation due to an underlying fear of the experimenter (or software) manipulating the price after the bid is made.

The elicited WTP allow us to test whether farmers deemed riskier ex-ante are willing to pay more for insurance, thus informing the composition of demand for products should these be released commercially. In addition, before conducting the BDM exercise, the participant was requested to choose one of his/her plots to enroll in insurance should they purchase the product. This element of the study design allows us to compare plot characteristics (in particular those that proxy for the risk of crop damage) of the plot that the household chose to enroll with those of the household's other plots, informing the extent of adverse selection at the plot level in this context.

Table 2 compares the characteristics of households that participated in the baseline survey (column 1) to those from the WTP elicitation sample, separately for the sample of 636 farming households who did not participate in the WTP experiment (column 2) and the 100 households who did participate (column 3). Column (4) in turn summarizes the difference in means between the two samples. Although we observe a few differences in household and farmer characteristics, most differences are not statistically significant. The only exception is that selected households had slightly fewer members than non-selected households. Under the assumption that engagement during the initial season was not driven by unobserved characteristics that are uncorrelated with the observed characteristics presented in Table 2, the results from our analyses should be broadly applicable to the population of smallholder farming households in our study districts, as the sampling prior to the initial season was representative of this population.

We study two aspects of adverse selection: at the farmer level and at the plot level, each with its own estimation strategy. For the former, we posit that, under the presence of adverse selection, farmers with worse yields and farmers for whom experts detected higher damage in crop pictures (arguably the riskier ones) would be willing to pay relatively more for PBI insurance coverage. We implement this idea by estimating the following model via OLS

$$WTP_{vi}^{j} = \alpha^{j} + \beta Y_i + \epsilon_{vi} \qquad [3]$$

where WTP_{vi}^{j} represents the willingness to pay for product j (i.e., *WBI only*, *PBI only*, or *WBI* + *PBI*) by farmer i in village v, and Y_i is a variable that proxies for farmer riskiness. We use six alternative variables to account for farmer riskiness: Damage due to mismanagement, not due to mismanagement, and total damage as identified by the experts during the loss assessments, objective CCE yields for Rabi 2016/17, and self-reported Rabi 2015/16 yields and expected yields during a normal year self-reported by farmers during the baseline interview. All specifications include weather stations fixed effects.

To test for adverse selection at the plot level, we exploit the fact that, at the time of the WTP elicitation exercise, farmers were requested to select one single acre among their wheat plots for which to get insurance, and test whether the selected plots exhibit riskier characteristics relative to the farmer's other plots. In particular, we rely on the following model

$$Y_{vip} = \alpha + \beta D_{ip} + \epsilon_{vi} \qquad [4]$$

where Y_{vip} represents a given plot characteristic (e.g., distance to farmer's home or soil fertility) for plot p of farmer i in village v, and D_{ip} is a dummy that takes a value of 1 if plot p was selected by the farmer to receive insurance. We follow two strategies to estimate the above equation: through OLS and through a panel household-level fixed effects estimator. Standard errors are clustered at the household level.

4. Results

This section presents evidence on the strength of demand for PBI stemming from the WTP exercise and on the extent of information asymmetry problems observed during the initial Rabi 2016/17 season.

4.1. Experiment 1 - Moral Hazard

As discussed above, we assess whether PBI induces moral hazard on insured plots by comparing differences in input use, observed damage, and objective wheat yields between farmers randomly assigned to the control treatment arm (receiving weather-based insurance alone) and to the treatment arm (receiving picture-based coverage in addition to WBI). If being covered against damage visible in pictures motivated farmers to put less effort into crop management, we would expect lower average input usage, higher observed damage from experts, and/or lower yields for farmers in the treatment group.

Table 3 shows the coefficients, standard errors, and significance level for the treatment dummy in Equation 1 (Post estimator) and Equation 2 (ANCOVA estimator), across an array of outcome variables. Such coefficient directly captures the difference in each outcome variable between the treatment and control arms (where a positive value indicates the treatment arm has a higher value than the control arm).

Overall, Table 3 shows that the number of times farmers applied irrigation, fertilizers, pesticides, and herbicides, as well as the quantity of inputs applied, including the number of own, family, and hired labor days is statistically indistinguishable between the two treatment arms. The only exceptions are a slightly lower average number of applications of Diammonium phosphate (DAP) fertilizer and a slightly higher number of hours of female family labor by farmers with PBI coverage. While statistically significant, these differences are economically negligible and are in line to what would be expected under multiple hypothesis testing. In the case of DAP, in addition, the difference in number of applications is not reflected in the average quantity applied for this fertilizer. All in all, we conclude that at the most direct level of input usage we observe no evidence of moral hazard.

Now, it is possible that PBI induces moral hazard in ways not captured by input usage, for instance if farmers put less effort into weeding, fail to react to potential hazards in time, or actively try to portray higher damage than what they actually experience.[6] Hence, we also test for moral hazard in a second set of outcome variables, which are objectively measured instead of self-reported. The bottom panels of Table 3 compare total observed crop damage, including damage due and not due to mismanagement (as estimated by agronomic experts during loss assessments at the end of the agricultural season), and wheat yields (measured through crop cutting experiments) between treatment arms. Again, we find no significant effect of PBI coverage on either assessed damage or yields, providing further evidence that farmers did not seem to strategically worsen their crop management to receive insurance payouts.

We conducted a series of robustness checks to confirm the validity of the above results.[7] First, when farmers took pictures of their fields through the KisanCam app, a series of questions came up in the screen asking farmers whether they had applied any inputs or experienced any damage since the last picture taken. Such high-frequency data, while subject to lower recall bias, is unfortunately much noisier. Indeed, no differences are found when using these variables as outcomes in our framework, with the only exceptions of slightly higher number of applications of fungicides and pesticides in the treatment arm, which is contrary to the moral hazard hypothesis.

Second, while the results above relate to the plot covered by insurance, farmers were allowed to take pictures for more than one of their plots. It is possible, then, that farmers did not remember exactly which of their plots was insured, and that they changed input use or exerted less effort in some of their other plots. Nonetheless, when using specifications focusing on outcome variables

[6] The latter, however, is technically insurance fraud and not moral hazard. While these are quite difficult to disentangle empirically, the analyses described would capture either of these.

[7] Due to space considerations, these are unreported but available on request from the authors.

measured for the farmer's other plots, the results are qualitatively similar as when focusing on the main insured plot (that is, we observe no effect of treatment also for the farmer's other plots).

Third, and as discussed above, we focus on intent-to-treat estimates of differences in outcome variables for the treatment and control group, including all survey farmers invited to enroll in insurance and take pictures; even though not all of them did enroll, and even though not all farmers enrolled in insurance may have been fully aware of their insurance coverage, since insurance was provided for free. To control for this, we constructed two alternative "treatment" variables: (i) an indicator taking the value of 1 if a farmer in either treatment arm indicated that they held insurance coverage against damage visible in the pictures they took, and (ii) an indicator taking the value of 1 if a farmer complied with the conditions outlined at the beginning of the agricultural season to receive insurance coverage, which included belonging to the treatment arm where farmers were provided WBI + PBI, and taking 3 or more pictures of their plot throughout the season.[8] The ITT estimator is preferred as it is not subject to selection bias, but in this robustness check, we may increase our statistical power to find an effect of PBI on farmer behavior. To overcome potential selection bias, a final robustness check uses a 2SLS instrumental variable specification where the indicator for believing to be insured against visible damage in pictures was instrumented through the random treatment assignment.

When using these two alternative treatment variables, significance patterns remain very similar to the ITT ones: "treated" farmers applied DAP slightly less often and relied on a slightly higher number of days of female family labor. However, we observe a few exceptions: "treated" farmers —as identified under both alternative indicators—, applied a higher quantity of urea and relied more on own labor and hired male labor; and farmers who believed to be covered against visible damage through their pictures applied a lower quantity of pesticides in their covered plots. While we find more differences between outcomes of treated and untreated farmers when using these alternative treatment indicators, most of these are not consistent with moral hazard or fraud (i.e., exerting more effort in terms of labor or applying higher amounts of fertilizer in plots insured with PBI). Also, while treatment assignment was determined at random, the alternative indicators

[8] In a randomly selected subset of villages in the treatment arm, an additional condition is added for this indicator to take on a value of 1 – that the farmer did not burn paddy stubble ahead of wheat planting – since in this subset of villages, farmers would have lost their insurance coverage if they burnt paddy residues. This last condition was related to a parallel experiment on climate-smart agriculture to study to effects of an incentive not to burn paddy residues. For more information, see Kramer and Ceballos (2018).

suffer from farmer selection, and could thus be correlated with other characteristics leading farmers to a better understanding of the conditions under which the insurance product was provided or their willingness to comply with the protocol. Reassuringly, in our 2SLS instrumental variable specifications, all coefficients except for the number of applications of DAP, are statistically indistinguishable from zero.

In sum, regardless of whether we analyze self-reported input usage, objectively measured yields, or damage assessed by agronomic experts, we find no evidence that farmers with PBI coverage reduce their efforts in response to having coverage against damage visible in pictures. Thus, at least in this specific context and during this first season, one of the main weaknesses often attributed to indemnity-based insurance — moral hazard — did not seem to have played a role.

4.2. Experiment 2 - Adverse selection

This final section addresses the issue of adverse selection, or the tendency for an insurance product to be purchased by riskier farmers (who value it the most, since they expect the highest payouts), potentially inducing insurance companies to raise premiums, crowding out less risky farmers and threatening the sustainability of the product. We first describe the levels of willingness to pay (WTP) for WBI and PBI, followed by a discussion of whether WTP is associated with a farmer's riskiness, and whether farmers selectively enrolled higher-risk plots into insurance.

4.2.1. Levels of willingness to pay

Figure 2 presents the average willingness to pay for each of the four products offered in the second experiment, based on the amount that farmers wrote down as the maximum amount they would pay for each product in the final, real-stakes round. Farmers seem to value the enhanced coverage provided by PBI as a standalone product. While the average farmer is willing to pay 5.7 percent of the sum insured for the WBI only product, he is willing to pay 6.7 percent for the PBI only product, a statistically significant increase in WTP of 17.7 percent. Moreover, farmers show interest in the bundled product, with an average WTP of 8.1 percent of the sum insured (Rs. 1,052), arguably related to the complementarity between the two insurance products, where PBI can provide coverage for visible damage in a time-lapse of pictures and WBI can help close the coverage gap in terms of non-visible damage. Contrary to our expectations, farmers do not seem to strongly dislike having to take pictures. The willingness to pay for the WBI + pictures product—

which requires farmers to take pictures of their crops regularly throughout the Rabi season—is only 0.2 percentage points lower than that of WBI only, an economically-small and statistically-insignificant difference.[9]

The average WTP presented in Figure 2, however, conceals the extent of heterogeneity in farmers' valuation and does not allow to understand demand in real market conditions at different premium rates. Figure 3 therefore shows an aggregate demand curve for each of the four products offered to farmers. Demand is consistently stronger for PBI only (relative to WBI only), and demand for the bundled product (WBI + PBI) is well above that for the standalone products, across a wide range of premium rates. Nonetheless, without government subsidies, take up would be low. During the Rabi 2016/17 season, HDFC Ergo offered the WBI only and the WBI + PBI products at 24 percent and 29 percent of the sum insured, respectively. Figure 3 shows that at these premium rates, no farmer would be interested in purchasing the product. During the more recent Rabi 2017/18 season, the first season's experience led HDFC Ergo to design a modified WBI + PBI product with a new pricing method, lowering premiums to 14.5 percent of the coverage amount; but even at those premiums, less than ten percent of farmers would be willing to purchase PBI.

While such dim levels of demand for insurance may seem discouraging, they need to be regarded in the general context of crop insurance in India. Under the PMFBY, farmers can purchase insurance for wheat at 1.5 percent of the sum insured per season, creating an implicit anchor value for other crop insurance premiums, which may have biased farmers' WTP downwards. At the same time, if PBI were to be included (as a top-up product for additional coverage) under the PMFBY umbrella, government premium subsidies could be reduced such that farmers pay a subsidized out-of-pocket premium rate. This could be for instance 5 percent of the sum insured, equivalent to premiums paid for insurance products for commercial crops. This could be done without significantly crowding out demand, given that the demand for PBI only and bundled products is less price sensitive than it is for the WBI only product.[10]

[9] This finding is in line with anecdotal evidence from farmers' informal conversations with field staff, where some farmers pointed out to an opposite effect: visiting the field more often is of value to them since it allows them to identify issues with the crop and thus initiate required actions earlier.

[10] In fact, in the state of Odisha, the PMFBY, HDFC Ergo, Dvara E-Registry and IFPRI are currently piloting the use of smartphone pictures for settling insurance claims for localized damage, mid-season adversities and post-harvest losses; effectively providing PBI without increasing either total insurance premiums or farmers' contributions.

4.2.2. Farmer-level adverse selection

Table 4 shows ordinary least squares estimates of farmers' WTP for the *WBI only*, *PBI only*, and *WBI+PBI* products as a function of six dummy variables capturing different elements of crop damage and yields, interpreted as proxies for farmer riskiness. Each cell in the table represents a separate specification, showing only the estimated coefficient and its associated standard error for each alternative variable. In the presence of adverse selection, riskier farmers (those with lower yields or higher levels of damage) should be willing to pay more for insurance coverage than less risky ones. However, we do not observe a significantly higher willingness to pay among farmers with higher visible damage (as independently assessed by agronomic experts) or lower Rabi 2015/16 and 2016/17 yields for any of the three types of insurance coverage.[11] Testing for differences in point estimates, Columns (4) and (5) indicate that in relation to the *WBI only* product, point estimates for insurance products that include PBI coverage are not systematically higher in the case of damage variables, or lower in the case of yield variables, meaning that PBI does not worsen the risk pool relative to existing index products.

The first five variables in Table 4 represent different measures of a farmer's yield or damage in the preceding season, which could potentially affect WTP through a behavioral mechanism known as salience effect or recency bias. If a farmer's recent losses were to affect his subjective probability of expected losses for the upcoming season, this could bias the WTP for insurance of farmers with higher levels of damage or lower levels of yield. To circumvent such bias, the last variable in Table 4 relies on farmers' self-reported expected yields under a normal year and, as such, should not be affected by behavioral biases related to recent events. As for the variables related to the preceding season, farmers reporting to expect lower yields also do not show a statistically significant higher WTP for insurance products, and the tests of differences in Columns (4) and (5) show no statistical differences for these coefficients between products. Combined, these findings indicate that additional PBI coverage does not raise the incidence of selection on a farmer's risk profile.

Such results are reassuring and indicate no evidence for the potential of adverse selection, at least during this initial season. We note, however, an important point before concluding this

[11] The significant coefficient for Rabi 2015/16 self-reported yields for the *PBI only* WTP has the opposite sign to what would be implied by adverse selection: less risky farmers (those with higher yields) are willing to pay more for this insurance product.

section. The usual claim of index products not being subject to adverse selection is only relevant from the insurer's point of view: since payouts are determined by an objective index and not by the insured's losses, covering a riskier pool of farmers does not raise the payout probability in any way. In other words, the difference between index and indemnity products lies in that the loss ratio of index products is not affected by changes in the underlying risk pool.

However, this does not necessarily hold from the insured's point of view. It is certainly possible that farmers more exposed to risk value an insurance product more and thus end up being overrepresented in the pool of farmers who contract it. This would be true for any insurance product, index or otherwise. In this sense, it is reassuring to see that more risky farmers in our sample are not willing to pay more for insurance than less risky farmers, regardless of whether they are offered WBI or PBI.[12]

4.2.3. Plot-level adverse selection

In this section we explore the evidence for adverse selection at the plot level, by testing whether the plot that a farmer chooses to enroll into insurance is of lower quality or more prone to suffer damage than his or her remaining plots. To that end, we conduct both ordinary least squares (OLS) and household fixed effects panel regressions, treating a plot as the unit of observation, and using a dummy variable indicating whether a plot was selected to be enrolled in insurance as our independent variable. We model a range of plot characteristics as dependent variables against this dummy variable. Table 5 shows the results of this analysis, where each cell in the table corresponds to the coefficient of the dummy variable estimated for the corresponding outcome variable indicated in the first column.

First, although the insurance product was meant to cover one single acre, farmers tend to enroll larger plots. This could be related to a plot needing to be large enough to fit in the full picture frame, to larger plots being the ones considered most important by the farmer, or simply due to misunderstanding of the insurance conditions. Second, farmers choose plots located closer to their home (though this variable is only significant in the household fixed effects panel regression),

[12] An exception would of course be that, if farmers regarded index products as providing lower insurance value than indemnity ones due to basis risk, adverse selection into these could turn out to be lower than for indemnity ones. While in our analyses this would be reflected as higher coefficients for products with PBI coverage, it would actually be indicative of high perceived basis risk in WBI leading to a lack of incentives to adverse select into this type of insurance, as opposed to the indemnity nature of PBI per se bringing in adverse selection.

perhaps because they will need to visit that plot more often to take repeat pictures. Neither plot size nor distance to home are, however, characteristics that would normally imply a higher level of riskiness, and thus we do not take them as evidence of plot-level adverse selection. For variables potentially related to a plot's exposure to risks—such as how far the plot is from an irrigation source, previous year's yields, soil type, fertility and drainage, and sales and rental value—we find no statistically significant differences between plots selected for insurance and others. Moreover, the magnitude of the point estimates for these differences is small. All in all, the available evidence for our study sample does not support the presence of plot-level adverse selection.

5. Conclusions

Digital technologies such as smartphones and satellite remote sensing are promising tools to reduce information asymmetries in insurance markets and provide high-quality insurance to underserved populations that depend on agricultural incomes for their subsistence. For instance, by relying on pictures taken by farmers using inexpensive smartphone cameras, PBI can provide insurers with eyes on the ground to verify losses at minimal cost and monitor crop management. However, since PBI pays out according to a farmer's individual visible losses, and since insurers may not be able to observe an individual farmer's effort or exposure to risk through the smartphone images, this digital technology may not be able to fully overcome traditional information-asymmetry issues from indemnity insurance. As a result, moral hazard or adverse selection may arise, which could damage the sustainability of the insurance scheme in the short run or increase premiums to unsustainable levels in the long run.

In this paper, we use data on input use, damage, and yields, combined with experimental variation in indemnity-based insurance coverage, to test for moral hazard; followed by an analysis of willingness to pay elicited for different types of insurance products to test for the presence of adverse selection. We find no evidence for PBI inducing moral hazard. Farmers randomly offered an insurance product with the more comprehensive PBI coverage do not seem to lower the frequency at which they apply irrigation or agricultural inputs (fertilizer, pesticides, or herbicides), nor the quantity of inputs or agricultural labor used during the cropping season. Moreover, no differential crop health conditions are found from either independent damage assessments carried out by agricultural experts or from objective yields measured through crop cutting experiments before harvest. These results are confirmed through a series of robustness checks conducted using other sources of data and based on alternative definitions of the comparison groups.

Further, although we find that farmers are willing to pay more for PBI than for more traditional weather index-based products, we find no evidence of PBI inducing adverse selection. Using six alternative proxies of farmer riskiness, riskier farmers do not value either weather index- or picture-based insurance products differentially more. In addition, farmers do not seem to choose riskier plots for insurance, as captured through survey data on geographic and soil characteristics of a farmer's entire set of plots. Nevertheless, multiple factors might be at play in farmers' decisions around insurance, some of which may be inducing advantageous selection (less riskier farmers valuing insurance more), which could offset any adverse selection. Importantly, the increased valuation for PBI relative to WBI is not higher among riskier farmers. We take this as evidence that PBI, closer in nature to an indemnity product, does not seem to bring about adverse selection in a stronger way than existing index products.

The absence of evidence on moral hazard or adverse selection during the initial rollout season for PBI, however, does not imply evidence of absence in the long term. The PBI approach may indeed be well suited to deter moral hazard and/or fraud by asking farmers to take pictures regularly, which may give them the impression that the insurance company is watching them and that they cannot reduce efforts or tamper with the pictures without being noticed. Nevertheless, as farmers become more acquainted with the product, moral hazard and adverse selection may arise over time. Testing for such mechanisms thus remains important in the monitoring and evaluation of innovative insurance products including PBI, and will continue to receive special emphasis in ongoing impact evaluations of such an approach. At the same time, our WTP measures indicate that demand for any of the insurance products that were offered will remain well below likely commercial premiums, and the first-order objective would need to identify innovations increasing demand rather than discouraging investments in innovations that could potentially be prone to moral hazard and adverse selection.

In conclusion, the results presented in this study speak to the sustainability of indemnity-based insurance unlocked by technological innovations, such as the PBI approach. Our findings of higher WTP for such insurance, combined with the absence of moral hazard and adverse selection in the short term, suggest that a digital-only indemnity product for agricultural insurance can be a working alternative or complement to other more commonly offered insurance products. In particular, PBI can offer similar advantages to those provided by traditional indemnity insurance, including better understanding and individual damage estimation, at a considerably lower cost. In addition, when compared with index insurance products, such insurance can offer lower basis risk with minimal concerns from information asymmetries. Despite these advantages, however, WTP for this product remains low. Considering that index insurance products implemented in the past decades have suffered from a similar lack of demand, our findings suggest that more emphasis should be placed into identifying insurance innovations that can overcome some of index insurance's main weaknesses and focus on fostering their demand, putting aside cynicism stemming from a direct comparison with index insurance's marketing ploys.

Tables and Figures

Table 1. Summary statistics and tests of balance

	Full Sample		WBI + pics		WBI+PBI		Diff.	*p*-value
	Mean	SD	Mean	SD	Mean	SD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Farmer characteristics								
Age of farmer	39.14	11.77	39.48	12.00	38.81	11.85	-0.621	0.5521
Farmer is male	0.999	0.037	1.000	0.000	0.997	0.053	-0.003	0.1662
Scheduled/other backward caste	0.102	0.303	0.126	0.332	0.088	0.283	-0.035	0.2623
Has some tertiary education	0.438	0.496	0.439	0.497	0.437	0.497	-0.003	0.9119
Farmer is married	0.864	0.343	0.872	0.335	0.851	0.357	-0.02	0.2769
Farmer has a data plan	0.686	0.464	0.687	0.465	0.668	0.472	-0.021	0.4221
Takes pictures often	0.774	0.418	0.761	0.427	0.794	0.405	0.032	0.1881
Household size at baseline	6.240	2.583	6.222	2.626	6.220	2.526	0.007	0.9628
Nr. Organizations	0.780	0.790	0.806	0.769	0.786	0.816	-0.021	0.6499
Panel B: Farming characteristics								
Nr. years of farming experience	15.592	10.463	16.165	11.19	15.206	10.043	-0.873	0.2970
Received training in farming	0.088	0.284	0.091	0.288	0.087	0.283	-0.002	0.8969
Number of plots	2.36	0.666	2.356	0.624	2.355	0.704	0.003	0.9379
Total area of plots (acres)	8.845	3.981	9.15	3.990	8.49	3.938	-0.674	0.0167**
% of land that the farmer owns	89.336	24.582	89.136	25.55	89.087	24.306	-0.259	0.8737
% with rice in Kharif 2015	0.856	0.322	0.862	0.329	0.848	0.323	-0.016	0.4000
% with wheat in Rabi 2015/16	0.963	0.132	0.97	0.121	0.96	0.141	-0.010	0.4194
Yield Rabi 2015/16 (quintals/acre)	19.593	2.104	19.773	2.169	19.495	2.073	-0.280	0.1815
Has burned crop residue	0.769	0.422	0.752	0.432	0.774	0.419	0.023	0.4901
Distance of plot to home (min)	16.331	20.016	15.222	17.97	17.334	21.623	2.002	0.1115
Distance of plot to WS (km)	3.488	1.877	3.415	2.094	3.429	1.571	0.128	0.714
Panel C: Financial access								
Has crop insurance through KCC	0.048	0.213	0.046	0.209	0.045	0.208	0.001	0.9604
Borrowed money for Rabi 2015/16	0.837	0.37	0.846	0.361	0.837	0.37	-0.012	0.5677
Has a bank account	0.984	0.127	0.986	0.119	0.98	0.139	-0.005	0.3615
Could get a loan if needed	0.746	0.436	0.744	0.437	0.743	0.438	-0.004	0.8916
Panel D: Risk mitigation								
Used laser land leveler	0.707	0.455	0.721	0.449	0.678	0.468	-0.044	0.1708
Used zero till with Happy Seeder	0.094	0.292	0.117	0.322	0.073	0.261	-0.044	0.0404**
Total N	736		366		370			

Note: This table shows the mean value of baseline farmer characteristics across the full study sample and the two treatment arms: WBI + pics and WBI + PBI. Column (8) presents p-values from a regression of the shown variable against a dummy variable equal to one if respondent is in the WBI+PBI treatment group, with weather station fixed effects, and standard errors clustered at the weather station level. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

Table 2. Sample selected for WTP experiments

	(1) Completed baseline	(2) Not selected for WTP (LA)	(3) Selected for WTP (LA)	(4) Difference (2) – (1)
PBI village	0.503	0.503	0.500	-0.003
	(0.071)	(0.073)	(0.115)	(0.101)
Age (in years)	39.143	39.245	38.490	-0.755
	(0.722)	(0.729)	(1.580)	(1.507)
Completed tertiary education	0.438	0.426	0.510	0.084
	(0.019)	(0.020)	(0.053)	(0.057)
Belongs to sched./OB caste	0.102	0.112	0.040	-0.071
	(0.029)	(0.031)	(0.031)	(0.035)
Landholdings (hectares)	8.845	8.871	8.683	-0.189
	(0.181)	(0.192)	(0.439)	(0.460)
Household size	6.240	6.313	5.780	-0.533*
	(0.119)	(0.119)	(0.282)	(0.282)
Perception of yield variability	3.993	4.002	3.940	-0.062
	(0.088)	(0.093)	(0.183)	(0.190)
Share of income from crops	0.835	0.838	0.815	-0.023
	(0.012)	(0.012)	(0.026)	(0.022)
Share of crop income from wheat	0.376	0.373	0.392	0.019
	(0.010)	(0.010)	(0.018)	(0.016)
Fraction of land planned to be sown with wheat	0.961	0.960	0.967	0.006
	(0.007)	(0.008)	(0.012)	(0.014)
Wheat yield Rabi 2015/16	19.570	19.579	19.516	-0.063
	(0.156)	(0.159)	(0.315)	(0.302)
Ever used laser land leveler	0.707	0.706	0.720	0.014
	(0.038)	(0.039)	(0.070)	(0.065)
Distance from plot to home (minutes)	15.900	15.640	17.459	1.819
	(1.186)	(1.072)	(3.126)	(2.760)
Owns insured plot	0.938	0.942	0.909	-0.033
	(0.011)	(0.010)	(0.034)	(0.034)
Takes pictures on phone often/very often	0.774	0.777	0.760	-0.017
	(0.025)	(0.027)	(0.045)	(0.048)
Has network signal often/very often	0.755	0.761	0.720	-0.041
	(0.030)	(0.029)	(0.070)	(0.065)
Number of farmers	736	636	100	

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 were not selected for the WTP elicitation exercise, and column 3 those that were selected. Column 4 shows the results of tests of equality of means between these groups. Standard errors, clustered at the village level, are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

Table 3. Input use, observed damage, and crop yields between treatment arms

	Post estimator			ANCOVA estimator			Mean of dep. var.
	(1)	(2)	(3)	(4)	(5)	(6)	
	Coeff.	Std. error	No. of obs.	Coeff.	Std. error	No. of obs.	(7)
Input Use (source: survey data)							
Number of applications							
Irrigation	0.062	(0.024)	688	0.062	(0.024)	686	2.761
Fertilizers: Urea	-0.005	(0.004)	688	-0.008	(0.004)	685	1.006
Fertilizers: DAP	-0.013***	(0.013)	688	-0.013***	(0.018)	686	0.058
Fertilizers: Potash	0.008	(0.017)	688	0.007	(0.011)	686	0.061
Fertilizers: Others	0.019	(0.035)	688	0.016	(0.035)	686	0.670
Pesticides	0.033	(0.016)	688	0.035	(0.015)	688	1.084
Herbicides	0.012	(0.076)	688	0.006	(0.076)	688	3.264
Quantity applied							
Total Fertilizers (kgs.)	0.809	(1.423)	688	0.849	(1.416)	686	112.2
Urea (kgs.)	-0.510	(1.010)	688	-0.599	(1.014)	687	50.89
DAP (kgs.)	0.725	(0.930)	688	0.763	(0.939)	688	59.62
Potash (kgs.)	0.594	(0.483)	688	0.514	(0.423)	687	1.725
Pesticides (gs.)	-6.939	(11.86)	688	-6.825	(11.88)	688	159.2
Herbicides (gs.)	-33.60	(25.79)	688	-33.860	(25.83)	688	311.6
Total Labor	-0.385	(1.063)	686	-0.339	(1.091)	681	19.91
Hired male labor (days)	-0.146	(0.274)	688	-0.082	(0.270)	686	4.832
Hired female labor (days)	-0.016	(0.021)	688	-0.016	(0.020)	687	0.029
Own labor (days)	-0.211	(0.881)	687	-0.209	(0.881)	687	13.29
Family male labor (days)	-0.009	(0.284)	687	-0.039	(0.285)	685	1.730
Family female labor (days)	0.0324*	(0.016)	688	0.0278*	(0.015)	685	0.000
Observed damage (source: expert loss assessments)							
Total Damage (%)	0.903	(2.076)	412	-	-	-	7.567
Damage not due to mismanagement (%)	0.766	(2.023)	412	-	-	-	6.016
Damage due to mismanagement (%)	0.106	(0.484)	412	-	-	-	1.030
Crop yields (source: crop cutting-experiments)							
Wheat yield (quintals per acre)	-0.347	(0.570)	436	-	-	-	19.80

Note: This table shows ordinary least squares coefficients for the effect of a treatment dummy identifying farmers receiving picture-based insurance coverage on different measures of input use, crop damage, and crop yields. All specifications include a constant and weather-station fixed effects. Standard errors, clustered at the village level, are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

Table 4. Willingness to pay for insurance and farmer riskiness

Variable	WTP for: (1) WBI only	(2) PBI only	(3) WBI+PBI	Test of differences: (2) - (1)	(3) - (1)	Num. of obs.
Damage due to mismanagement	20.848	23.748	30.053	2.900	9.204	97
	(19.594)	(22.613)	(25.824)	(9.011)	(12.167)	
Damage not due to mismanagement	-0.241	-2.514	-0.860	-2.273	-0.619	97
	(3.959)	(4.560)	(5.224)	(1.793)	(2.450)	
Total damage	1.582	-0.602	1.456	-2.184	-0.126	97
	(3.984)	(4.601)	(5.260)	(1.808)	(2.468)	
Rabi 2016/17 crop cutting yield	-5.041	0.225	13.907	5.267	18.948**	94
	(13.687)	(16.016)	(18.359)	(6.292)	(8.388)	
Rabi 2015/16 self-reported yield	36.500	44.266*	47.561	7.766	11.061	100
	(22.411)	(26.182)	(29.805)	(10.115)	(13.742)	
Expected yield during normal year	1.033	13.296	11.042	12.263	10.009	100
	(23.895)	(27.912)	(31.738)	(10.581)	(14.449)	
Mean of dependent variable	736	866	1,052	130	316	

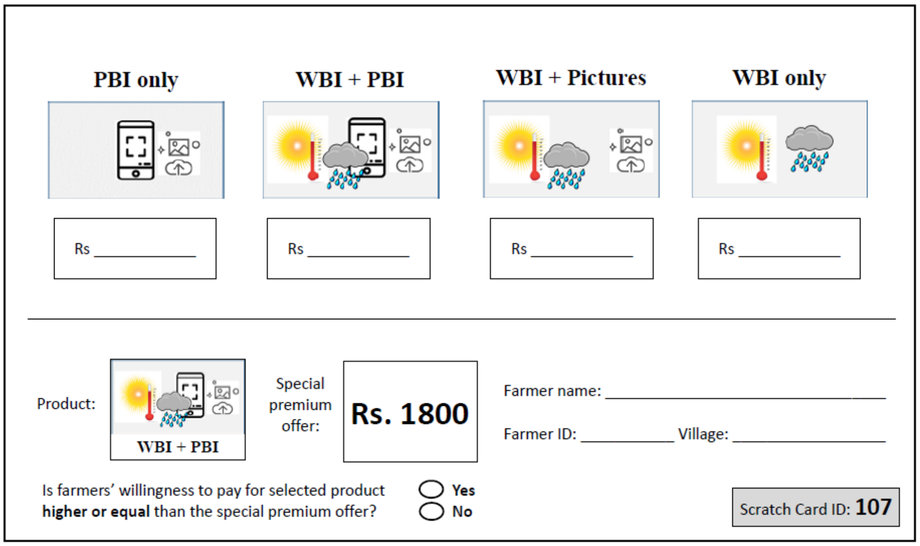
Note: This table shows ordinary least squares coefficients for the effect of six different proxies of farmer riskiness on farmer WTP for three alternative insurance products. Each cell shows the estimated coefficient for these variables from an ordinary least squares regression with WTP as dependent variable; a constant and weather-station fixed effects are included but not reported. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 5. Characteristics of plot selected for insurance

Variable	OLS	Household Fixed Effects	Mean of dep. var.	Num. of Obs.	Num. of HHs
Area (acres)	0.995***	0.838***	3.198	230	97
	(0.324)	(0.315)			
Distance to home (mins. walking)	-1.019	-2.964**	19.510	184	92
	(1.518)	(1.413)			
Distance to irrigation (mins. walking)	-0.462	-0.109	3.019	172	86
	(0.329)	(0.162)			
Yield in Rabi 2015/16 (quintals per acre)	-0.047	0.032	19.330	214	94
	(0.315)	(0.315)			
Sandy loam soil	-0.037	-0.012	0.619	184	92
	(0.043)	(0.034)			
Soil has *Good* or *Very Good* fertility	0.008	0.012	0.981	184	92
	(0.019)	(0.020)			
Less fertile than other plots	-0.020	-0.024	0.019	184	92
	(0.014)	(0.016)			
Soil has good drainage	0.004	0.012	0.962	184	92
	(0.029)	(0.030)			
Worse drainage than other plots	-0.026	-0.036	0.048	184	92
	(0.028)	(0.030)			
Sales value (lakh Rs. per acre)	0.150	0.099	23.190	230	97
	(0.655)	(0.299)			
Rental value (thousand Rs. per acre per year)	0.714	-0.138	38.690	230	97
	(0.573)	(0.157)			

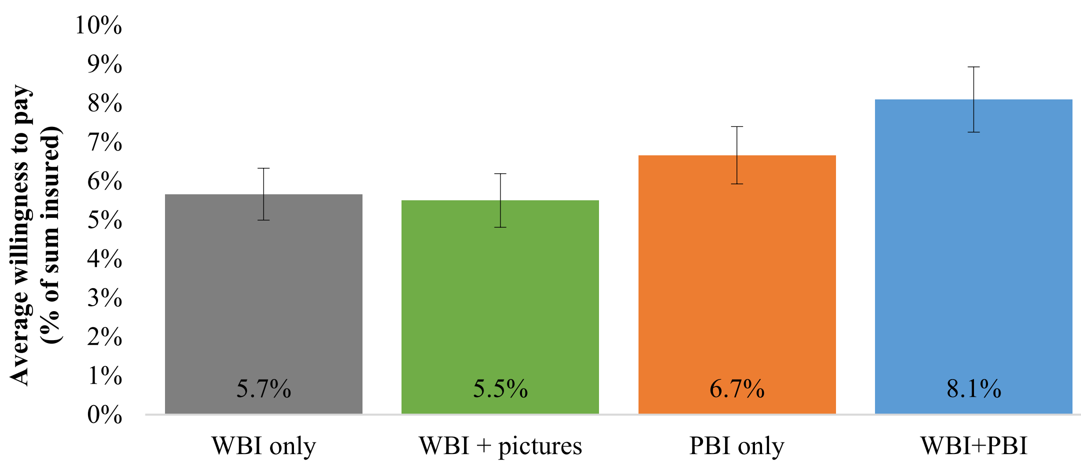
Note: This table shows the results from ordinary least squares (OLS, column 1) and panel household-level fixed effects (column 2) specifications using a number of soil characteristics as the dependent variable against a dummy variable indicating whether a plot has been selected for insurance. Each cell shows the estimated coefficient for this dummy variable. A constant is included but not reported. Standard errors, clustered at the household level, are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Figure 1 – Scratch card to elicit willingness to pay



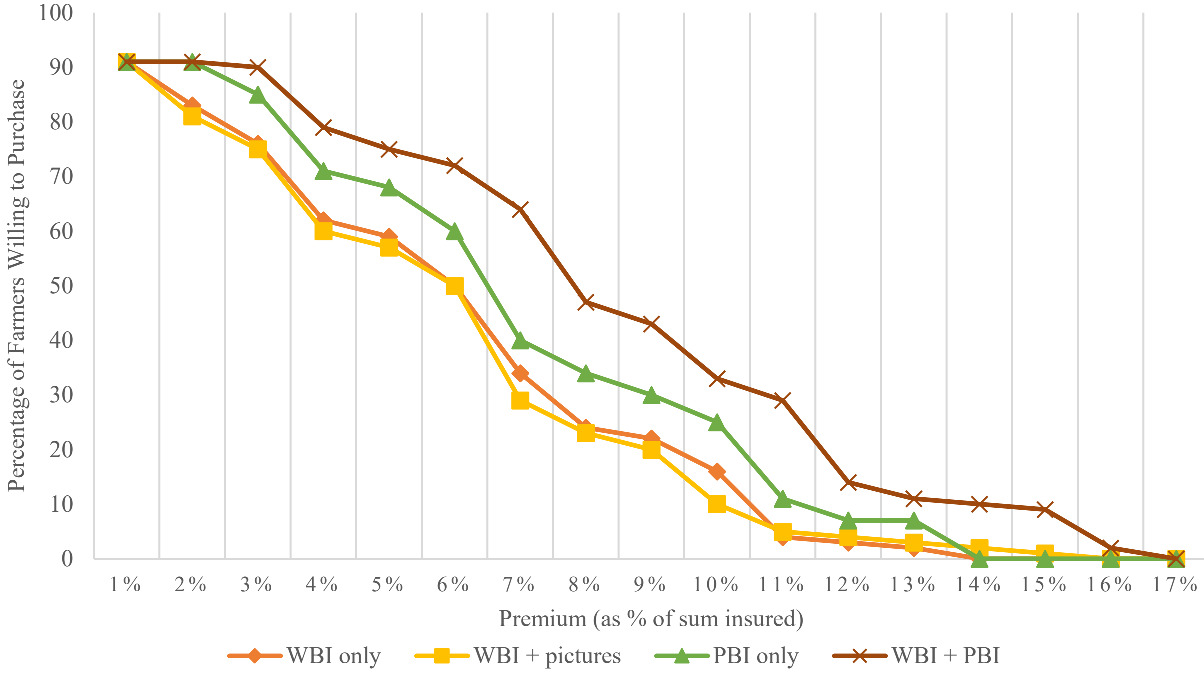
Note: This figure shows an example of a scratch card used to elicit willingness to pay in the field. The top half of the card shows pictorially the four alternative products for which farmers were being requested to state their maximum WTP, the order of which was random across cards. The bottom half of the card includes two boxes that contained a randomly-selected product and special premium offer and were covered with metallic scratch-off ink.

Figure 2 – Average willingness to pay by product



Note: This figure shows the average willingness to pay, as a percentage of the sum insured, for four alternative insurance products offered to farmers. Confidence intervals at the 95 percent level are shown for each bar.

Figure 3 – Demand curves by product



Note: This figure shows demand curves for four alternative insurance products offered to farmers. The curves are constructed from individual farmer WTP for each product and show the percentage of farmers willing to purchase the product at each hypothetical premium.

References

Akerlof, G. (1970). "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism", *Quarterly Journal of Economics,* 84(3), pp. 488-500.

Bageant, E.R. and C.B. Barrett (2017). "Are There Gender Differences in Demand for Index-Based Livestock Insurance?" *Journal of Development Studies* 53(6): pp. 932-952.

Banerjee, A., E. Duflo and R. Hornbeck (2014). "Bundling health insurance and microfinance in India: There cannot be adverse selection if there is no demand," *American Economic Review*, 104(5), pp. 291-97.

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.

Becker, G.M., M.H. Degroot and J. Marschak (1964). "Measuring Utility by a Single-Response Sequential Method," *Systems Research and Behavioral Science* 9(3): pp. 226–232.

Benami, E., Jin, Z., Carter, M.R., Ghosh, A., Hijmans, R.J., Hobbs, A., Kenduiywo, B. and Lobell, D.B. (2021). "Uniting Remote Sensing, Crop Modelling and Economics for Agricultural Risk Management," *Nature Reviews Earth & Environment* 2(2): pp.140-159.

Cariappa, A.G., G.B. Lokesh and G.B. Ramesh (2017). "Progress of Crop Insurance and Pradhan Mantri Fasal Bima Yojana in India," *Agricultural Economics Research Review* 30.

Ceballos, F., B. Kramer and M. Robles (2019). "The Feasibility of Picture-Based Insurance (PBI): Smartphone Pictures for Affordable Crop Insurance," Development Engineering 4, 100042.

Chiappori, P.A. and Salanié, B. (2000). "Testing for asymmetric information in insurance markets," *Journal of Political Economy*, 108(1), pp. 56-78.

Coble, K.H., Knight, T.O., Pope, R.D. and Williams, J.R. (1997). "An Expected-Indemnity Approach to the Measurement of Moral Hazard in Crop Insurance," *American Journal of Agricultural Economics* 79(1): pp.216-226.

Cohen, A. and P. Siegelman (2010). "Testing for Adverse Selection in Insurance Markets," *Journal of Risk and insurance* 77(1): pp. 39-84.

Cole, S., 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): pp. 104–135.

Cole, S., X. Giné and J. Vickery (2017). "How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment," *Review of Financial Studies* 30(6): pp. 1935-1970.

Cole, S., D. Stein and J. Tobacman (2011). "What Is Rainfall Index Insurance Worth? A Comparison of Valuation Techniques," mimeo.

De Meza, D. and Webb, D.C. (2001). "Advantageous Selection in Insurance Markets," *RAND Journal of Economics*: pp.249-262.

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

Doiron, D., Jones, G. and Savage, E. (2008). "Healthy, Wealthy and Insured? The Role of Self-Assessed Health in the Demand for Private Health Insurance," *Health economics* 17(3): pp. 317-334.

Finkelstein, A. and McGarry, K. (2006). "Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market," *American Economic Review* 96(4): pp. 938-958.

Hazell, P., C. Pomareda and A. Valdes (1986). "Crop Insurance for Agricultural Development". Baltimore: Johns Hopkins University Press.

He, J., R.M. Rejesus, X. Zheng and J.M. Yorobe Jr (2018). "Advantageous Selection in Crop Insurance: Theory and Evidence," *Journal of Agricultural Economics*, 69(3), pp. 646-668.

He, J., X. Zheng, R.M. Rejesus and J.M. Yorobe Jr (2017). "Moral Hazard and Adverse Selection Effects of Cost-of-Production Crop Insurance with Input Monitoring: Evidence from the Philippines," mimeo.

Horowitz, J.K. and Lichtenberg, E. (1993). "Insurance, Moral Hazard, and Chemical Use in Agriculture," *American Journal of Agricultural Economics* 75(4): pp. 926-935.

Jensen, N.D., A.G. Mude and C.B. Barrett (2018). "How Basis Risk and Spatiotemporal Adverse Selection Influence Demand for Index Insurance: Evidence from Northern Kenya," *Food Policy* 74: pp. 172-198.

Just, R.E., L. Calvin and J. Quiggin (1999). "Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives," *American Journal of Agricultural Economics* 81(4): pp. 834-849.

Kramer, B. and Ceballos, F. (2018). “Enhancing Adaptive Capacity Through Climate-Smart Insurance: Theory and Evidence from India,” in 2018 Conference, July 28-August 2, 2018, Vancouver, British Columbia (No. 275926). International Association of Agricultural Economists.

Makki, S. and A. Somwaru (2001). “Evidence of Adverse Selection in Crop Insurance Markets,” *Journal of Risk and Insurance* 68(4): pp. 685-708.

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

McKenzie, D. (2012). “Beyond Baseline and Follow-Up: The Case for More T in Experiments,” *Journal of Development Economics* 99(2): pp. 210-221.

Parlasca, M.C., Johnen, C. and Qaim, M., 2022. Use of mobile financial services among farmers in Africa: Insights from Kenya. *Global Food Security*, 32, p.100590.

Polimeni, R. and D. Levine (2012). “Prices Matter: Comparing Two Tests of Adverse Selection in Health Insurance” Working Paper 135-12, Institute for Research on Labor and Employment, UC Berkeley, December 2012.

Rao, X. and Zhang, Y. (2020). “Livestock Insurance, Moral Hazard, and Farmers’ Decisions: A Field Experiment among Hog Farms in China,” *The Geneva Papers on Risk and Insurance-Issues and Practice* 45(1): pp. 134-156.

Smith, V.H. and Goodwin, B.K. (1996). “Crop Insurance, Moral Hazard, and Agricultural Chemical Use,” *American Journal of Agricultural Economics* 78(2): pp. 428-438.

Stein, D. and J. Tobacman (2016). “Weather Insurance Savings Accounts,” *Geneva Papers on Risk and Insurance-Issues and Practice* 41(4): pp. 677-700.

Suri, T. and Jack, W., 2016. The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), pp.1288-1292.

Townsend, R.M. (1994). “Risk and Insurance in Village India,” *Econometrica*, pp. 539-591.

Wu, S., Goodwin, B.K. and Coble, K. (2020). “Moral Hazard and Subsidized Crop Insurance,” *Agricultural Economics* 51(1): pp. 131-142.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org