Enhancing adaptive capacity through climate-smart insurance: Theory and evidence from India

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Bundling agricultural insurance with climate-smart technologies and practices (CSA) can help improve risk management for smallholder farmers. This paper analyzes how bundling affects demand for insurance and CSA. Calibrating index insurance parameters to CSA payoff profiles increases the demand for insurance, but only when basis risk is low, and these effects of reducing basis risk itself. This raises the question how to bundle insurance products that leverage new technologies to provide indemnity insurance coverage with minimal basis risk. We therefore study the effect of bundling indemnity insurance with CSA technologies. Specifically, in a field experiment in India, we test whether conditioning insurance payouts on not burning residues improves residue management as a CSA technology. We find that this is the case, suggesting that indemnity insurance can help promote CSA technology adoption, but we also discuss shortcomings of this bundling approach, and identify potential alternatives to combine indemnity insurance and CSA technologies into a complementary risk management bundle.

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JEL Codes: G22, O13

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Abstract

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Keywords: insurance; conservation agriculture; experiment; mechanism design; India
JEL codes: D81, G2, O13, Q14, Q54

1 Introduction

Most of the world's poor depend on agriculture for their livelihoods, and are vulnerable to the effects of natural disasters such as floods, droughts, and extreme temperatures on crop production. For instance, Carleton (2017) estimates that rising temperatures in the last three decades have been responsible for over 59,000 suicides or 6.8 percent of India's increasing suicide rates since 1980. Looking ahead, the issue is expected to exacerbate as extreme weather events occur more frequently in the face of climate change. According to the Intergovernmental Panel on Climate Change (IPCC), climate change will increase crop yield variability, and a 2°C temperature increase will negatively impact production of the major crops grown globally, in particular in countries at lower latitudes, which are generally countries with higher poverty rates and lower food security (Porter et al., 2014).

Policymakers are hence increasingly seeking for ways to reorient agricultural systems to widespread changes in rainfall and temperature patterns, and climate-smart agriculture (CSA) is one approach through which agricultural systems can effectively respond to climate change (Lipper et al., 2014).[1] CSA incorporates technologies, policies, institutions and investments, both on-farm and beyond the farm, to increase the adaptive capacity of farmers as well as the resilience and resource use efficiency in agricultural production systems. CSA technologies are typically meant to yield similar incomes as conventional modern agriculture under optimal weather conditions, whilst protecting incomes from suboptimal weather conditions. Examples include stress-tolerant seed varieties and conservation agriculture (CA), a system of practices in which farmers cover the soil permanently with mulch without tilling the land. In various contexts, CA has been shown to improve soil and crop properties, which enables more efficient use of natural resources and helps moderate soil temperatures (Hobbs, 2007).

This paper analyzes how to combine CSA technologies with weather index insurance such that the two instruments combined form a complementary risk management bundle. Several initiatives have been

[1] CSA promotes coordinated actions by farmers, researchers, private sector, civil society and policymakers towards climate-resilient pathways through four main action areas: building evidence; increasing local institutional effectiveness; fostering coherence between climate and agricultural policies; and linking climate and agricultural financing. There CSA approach is different from 'business-as-usual' in that it emphasizes the capacity to implement flexible, context-specific solutions, supported by innovative policy and financing actions (Lipper et al., 2014).

launched in the last two decades to expand coverage through affordable weather index insurance. Crop insurance is often cited as an instrument to promote high-return yet high-risk technology adoption for risk averse and credit-constrained farmers, and a number of case studies find indeed positive impacts of weather index insurance on technology adoption (Karlan et al., 2014; Cole et al., 2017, see e.g.). Carter et al. (2016) show that index insurance, when interlinked with loans, can boost adoption of these modern technologies in particular when farmers suffer high covariate risks and loans are highly collateralized. CSA however reduces exposure to weather risks and this could make it a substitute for weather index insurance.

At the same time, neither CSA technologies nor weather index insurance are perfect solutions to manage weather risk (Lybbert and Carter, 2015). CSA technologies generally reduce vulnerability to moderate weather events, but fail under extreme weather conditions, whereas insurance products are considered more appropriate to cover extreme events for which other risk management alternatives fail. By calibrating insurance indices properly to cover losses from extreme weather shocks, and not those from shocks that farmers can mitigate by adopting CSA technologies, insurance premiums can remain low without offering farmers partial insurance. Ward et al. (2015) find a higher willingness to pay for stress-tolerant cultivars when bundled with insurance, suggesting that there are complementarities between these different types of risk management products.

We therefore analyze the effects of such bundling on the demand for insurance and demand for CSA. Specifically, we are interested in answering two research questions. First, we will study the effect of bundling index insurance with CSA on demand for insurance and CSA. In this context, bundling means properly calibrating index insurance to match CSA payoff profiles. This might prove more difficult in a context of basis risk, meaning that the index is not perfectly correlated with actual losses, and we will hence vary the extent to which there is basis risk in our analyses.[2] Second, motivated by a trend to minimize basis risk and cover actual losses at the farm or even plot level, we analyze the effects of bundling indemnity insurance with CSA, by which we mean explicitly conditioning insurance payouts on CSA adoption. In indemnity

[2] Basis risk can arise for instance because indices are based on weather stations located far from the insured plot (spatial basis risk), or because farmers are sowing at a different time, meaning that their crop is at risk in a different period than assumed when constructing the index (temporal basis risk), or because the index covers one type of event (for instance drought) whereas farmers can suffer losses from various events that are not covered by insurance (design risk). Intuitively, one could imagine that adopting CSA could help cushion the negative effects of basis risk, as it offers protection in events whereby the index may (incorrectly) fail to trigger. At the same time, a product calibrated to trigger only under severe and extreme weather conditions might be more likely to miss these important events compared with a conventional product in the presence of basis risk.

insurance, deductibles will be in place to encourage good practices, and we will hence study the effect of bundling under different deductible levels.

We will answer these questions using both theory and a field experiment. We find that for index-based insurance products, in the absence of basis risk, bundling improves demand for insurance, and adopting CSA improves well-being over normal practice, indicating that there are complementarities between insurance (covering more extreme weather risks) and CSA (covering moderate risks). However, when there is basis risk, this prediction turns around; calibrating the product to trigger only in case of severe and extreme risks reduces the demand for insurance. Moreover, when adopting CSA technologies is costly, subsidized index insurance will crowd-out CSA technology adoption–regardless of whether indices are calibrated to match CSA payoff profiles. In a field experiment, we show that explicitly conditioning agricultural insurance on the visible adoption of climate-smart practices (not burning residues) significantly improves adoption. However, many farmers do not adopt better practices, leaving a large portion of farmers uninsured.

We conclude that reducing basis risk is imperative for improving risk management, and in particular, for bundling insurance with CSA technologies and insurance to be an effective strategy to improve adaptive capacity to climate change. Picture-based insurance, which makes payouts when there is damage visible in pictures of insured plots (Ceballos and Kramer, 2017), and satellite imagery-based yield predictions offer a promising alternative to reduce basis risk (Black et al., 2016b,a). However, these insurance products rely on indices that are in part under the control of farmers themselves, and aim to predict yields as closely as possible. As a result, these products aim at resembling indemnity insurance products, which traditionally suffered high transaction costs and moral hazard (Hazell et al., 1986).

Although transaction costs can be overcome by relying on remote sensing technologies, the question is still how to prevent moral hazard. Explicitly conditioning payouts on CSA technology adoption, for instance by bundling insurance with stress-tolerant seed varieties, is one way to overcome the moral hazard problem. Moreover, even without such bundling, satellite-based as well as the near-surface remote sensing technology employed in the present study increasingly enable insurance providers to condition insurance premium subsidies on desirable CSA practices and technologies. As such, products that intend to provide yield-based or indemnity insurance, with minimal basis risk and explicitly encouraging CSA adoption, offer a promising alternative to address the moral hazard problem, and improve risk management among smallholder farmers.

The remainder of this paper is structured as follows. In the next section, we describe our conceptual framework and theoretical predictions to show the effects of bundling index insurance and indemnity insurance with CSA. In Section 3, we describe a field experiment in which we tested the effects of conditioning insurance coverage on not burning harvest residues, including the study context, methods, data and results. Section 4 interprets our findings, discusses the implications, and provides potential areas for future research. The final section concludes.

2 Effects of bundling insurance with CSA: Theory

This section derives theoretical predictions of how bundling insurance with CSA affects demand for insurance and demand for CSA technologies and practices. We first describe a conceptual framework in which risk averse farmers decide whether to adopt CSA and insurance, improving adaptation to moderate and more severe weather risks, respectively. We then analyze for the case of index-based insurance how these decisions are affected by adjusting the index parameters to CSA payoffs, varying the degree of basis risk. Next, we will analyze the effects of conditioning yield-based insurance payouts on CSA adoption, varying the degree of the deductible imposed to limit moral hazard.

2.1 Conceptual framework

We model the decision whether to adopt insurance and CSA for risk averse farmers in a one-period framework. Farmers make these decisions by optimizing expected utility from consumption C:

$$\max_{d,\lambda} \mathrm{E}U(C(d,\lambda,\theta)) \tag{1}$$

whereby $d \in \{0,1\}$ indicates whether the farmer takes up crop insurance (one if insured and zero otherwise), $\lambda \in \{0,1\}$ indicates whether the farmer adopts CSA (one if adopting and zero otherwise), and θ represents the realization of weather conditions, which is unknown at the time of the decision. Farmers' utility function

$U(\cdot)$ is continuous, increasing ($U'(\cdot) > 0$), twice differentiable and concave ($U''(\cdot) < 0$), and in our numerical applications, we assume that the utility function exhibits constant relative risk aversion with the CRRA coefficient defined as $r > 0$.

Consumption in period t is determined by the following budget constraint:

$$C(d, \lambda, \theta) = Y_\theta^\lambda + d(I - \alpha \mathrm{E}[I]) - \lambda \beta Y_\theta^1 \tag{2}$$

whereby Y_θ^λ is the payoff from agricultural production, I represents insurance payouts, $\alpha \geq 0$ is the cost of the insurance policy (as a proportion of the actuarially fair insurance premium, $\mathrm{E}[I]$), and $\beta \geq 0$ the cost of adopting CSA (as a proportion of the payoffs under CSA). When $\alpha = 1$, the insurance product is offered at the actuarially fair premium. Common loading factors cited in the literature are around 30%, corresponding to $\alpha = 1.3$. Subsidies will reduce the premium below this level ($\alpha < 1.3$), and potentially below the actuarially fair premium ($\alpha < 1$).

We model the cost of adopting CSA proportional to payoffs instead of as a fixed cost so that adoption costs do not increase exposure to risk. This is a major departure from how modern high-risk high-return technologies are modeled. Those technologies are typically seen as fixed investments that generate higher yields–and can hence be profitable–under normal weather conditions, while resulting in comparable or worse yields–and causing income losses when taking the initial investment into consideration–under poor weather conditions. CSA should not reduce payoffs compared with normal practice under extreme weather conditions, and we therefore model the cost of adopting CSA as a proportion of realized payoffs from adopting CSA.

Note that we abstract from modeling liquidity constraints that prevent farmers from paying the premium. Our empirical application focuses on the case of India, which has a national insurance scheme in which the majority of insurance policies are combined with loans. Farmers can hence pay the premium at the time of loan repayment, when they have access to liquidity from selling their harvest, or from receiving insurance payouts. We also assume that farmers do not face price risk. India has a minimum support price scheme for major staple crops, and we indeed observe limited variation in prices received by farmers, making this a plausible assumption.

Payoffs. Agricultural payoffs Y_θ^λ depend on management practices λ and weather conditions θ as depicted in Figure 1. The dashed line indicates payoffs under normal practice ($\lambda = 0$), whereas the solid line indicates payoffs under CSA ($\lambda = 1$). Following evidence from agronomic trials, payoffs under CSA stochastically dominate payoffs under normal practice in this framework. Under normal weather conditions, $\theta \leq \theta^0$, payoffs are at their maximum level $\tilde{Y}$ regardless of agricultural practices. Moderate weather conditions, $\theta \in (\theta^0, \theta^1)$, reduce payoffs under normal practices, but crops under CSA are more resilient and suffer only once weather conditions become more severe, $\theta \in (\theta^1, \theta^2)$. In years with extreme weather conditions, $\theta \geq \theta^2$, payoffs are zero under both cropping systems.[3] We can summarize these payoffs as follows:

$$Y_\theta^\lambda = \max\left[\tilde{Y}\left(1 - \mathrm{I}_{[\theta \geq \theta^\lambda]}\frac{\theta - \theta^\lambda}{\theta^2 - \theta^\lambda}\right), 0\right]. \tag{3}$$

whereby $I_{\theta \geq \theta^\lambda}$ is an indicator that takes on value one if $\theta \geq \theta^\lambda$ and zero otherwise.

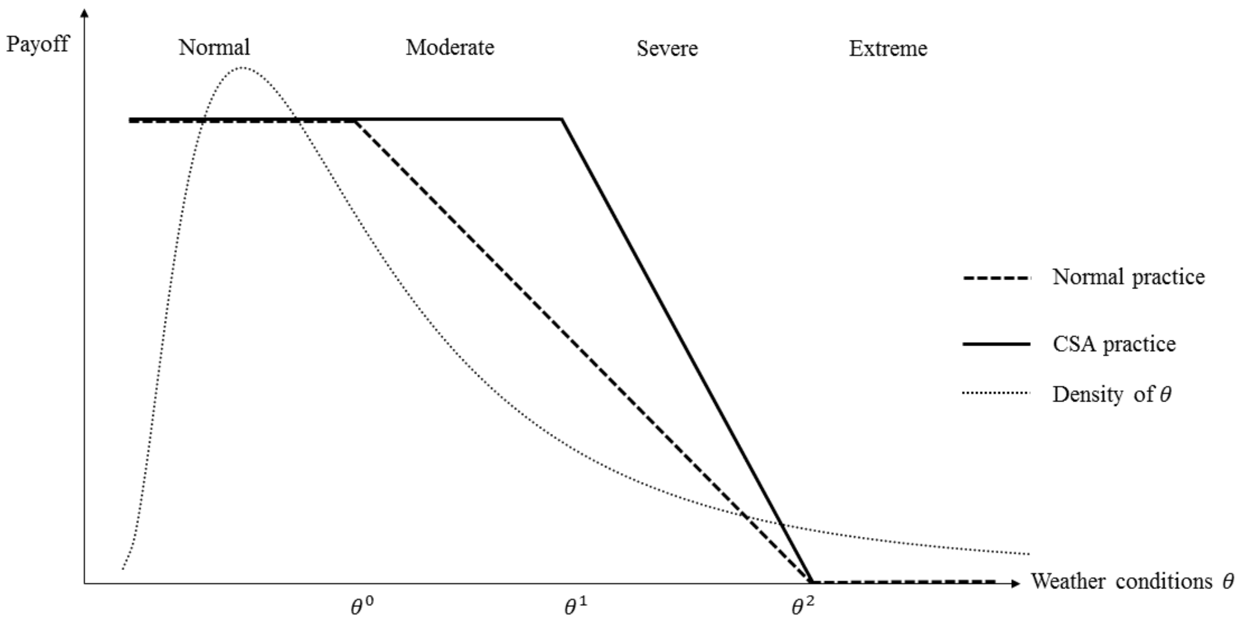
Index insurance. We will analyze both index insurance and indemnity insurance. Under index insurance, payouts do not depend on the farmer's actual management practices, but management practices to which the insurance product is tailored, which we denote Λ, which is equal to zero if the product is based on the assumption that farmers cultivate using normal practices, and equal to one under the assumption that farmers have adopted CSA. Moreover, instead of making payouts based on actual weather conditions observed on farmers' plots, the insurance product pays out based on an external proxy for damage from weather risk, ζ, for instance an index of high temperatures measured at a nearby weather station:

$$I^{Index} = I(\Lambda, \zeta) = \tilde{Y} - Y_\zeta^\Lambda \tag{4}$$

By bundling index insurance with CSA, we mean that we go from an insurance product that assumes

[3] This is consistent with the context described earlier. Conservation agriculture is associated with lower yields but also lower fertilizer, irrigation and labor usage, resulting in equivalent payoffs. It makes the crop more resilient as it improves soil moisture (providing better protection from moderate drought), reduces the canopy temperature of crops (protecting the crop from moderate heat), improves drainage (protecting production from excess rainfall), and strengthens roots (protecting the crop from lodging due to heavy winds combined with rains).

Figure 1: Density of weather shocks and payoffs depending on management practices



normal practice, with insurance payouts equal to $\tilde{Y} - Y^0_\zeta$, to a product that assumes farmers practicing CSA, with insurance payouts equal to $\tilde{Y} - Y^1_\zeta$.

Indemnity insurance. Under indemnity insurance, payouts depend on realized yields, which in turn are determined by CSA adoption, λ, and weather conditions, θ. A deductible δ is in place to minimize moral hazard in case insurance providers do not observe CSA adoption. Insurance payouts can be written as optimal yields minus deductible minus actual yields:

$$I^{Indemnity} = I(\lambda, \theta) = \max\left(\tilde{Y} - \delta - Y^\lambda_\theta, 0\right), \quad \delta \in [0, \tilde{Y}] \tag{5}$$

Without deductible, $\delta = 0$, the farmer receives the difference between payoffs under normal weather conditions versus his or her realized yields, which depend on management practices λ and weather conditions θ. Inserting this into the farmer's budget constraint, Equation (2), the farmer will consume a risk-free quantity equal to $\tilde{Y} - \alpha \mathrm{E}[I]$ if purchasing insurance ($d = 1$), versus Y^λ_θ if not purchasing insurance ($d = 0$).

When there is a deductible, $\delta > 0$, and realized payoffs are high relative to the deductible, $\tilde{Y} - Y^\lambda_\theta <$

δ, an insured farmer consumes an amount equivalent to his actual payoff minus the insurance premium, $Y_\theta^\lambda - \mathrm{E}[I]$, whereas if realized payoffs are low relative to the deductible, $\tilde{Y} - Y_\theta^\lambda > \delta$, insurance payouts are triggered and the farmer consumes optimal yields minus the deductible and the insurance premium, $\tilde{Y} - \delta - \alpha\mathrm{E}[I]$. We will vary the deductible in deriving our theoretical predictons. In the empirical section of this paper, we will set the deductible to 20 percent, which has been suggested as the minimum level of deductible to maintain in agricultural insurance (Hazell, 1992).

When bundling indemnity insurance with CSA, we will assume that payouts will be made conditional on the farmer adopting CSA as a mitigation strategy. In other words, the insurance product is available only for farmers who are adopting CSA. One example is, in case an insurance company is able to observe CSA practices while indemnifying losses (for instance residue burning in our empirical example with picture-based insurance), insurance payouts can be conditioned on such practices. An alternative example, in case ex-post observations are not possible, but ex-post bundling is an option, is to bundle the insurance policy with the purchase of a resilient seed variety.

Modeling risk. In the absence of basis risk, θ and ζ are perfectly correlated. When there is basis risk, agricultural payoffs and insurance payouts as determined by these two shock variables are imperfectly correlated.[4] We model the correlation between weather shocks θ and the index to proxy these shocks ζ by assuming that these variables follow a bivariate lognormal distribution with mean zero, standard deviation σ and correlation ρ:

$$\mathrm{Log}(\theta, \zeta) \sim N(0, \sigma, \rho) \tag{6}$$

In deriving theoretical predictions, we will fix σ but analyze the implications of different degrees of basis risk, whereby a zero correlation between observed and assumed weather shocks, $\rho = 0$, implies maximum basis risk, while a perfect correlations, $\rho = 1$, implies no basis risk.

[4] In theory, such basis risk is a concern mainly in applications of index insurance. We abstract in this paper from non-performance of indemnity products. Non-performance occurs when the insurer fails to make insurance payments to farmers who according to the insurance contract are eligible to receive insurance payouts. Conceptually, this can be interpreted as downside basis risk.

2.2 Effects of bundling index insurance with CSA

We first analyze to what extent calibrating index insurance to match payoffs under CSA practices improves the demand for insurance. We will abstract from CSA adoption costs, $\beta = 0$. Under this condition, farmers will always adopt CSA, since payoffs from practicing CSA stochastically dominate those from normal practices. This means that the farmer will purchase index insurance if and only if:

$$\mathrm{E}U(C(1,1,\theta)) > \mathrm{E}U(C(0,1,\theta)) \Leftrightarrow \mathrm{E}U(Y_\theta^1 + I - \alpha \mathrm{E}[I]) > \mathrm{E}U(Y_\theta^1)$$

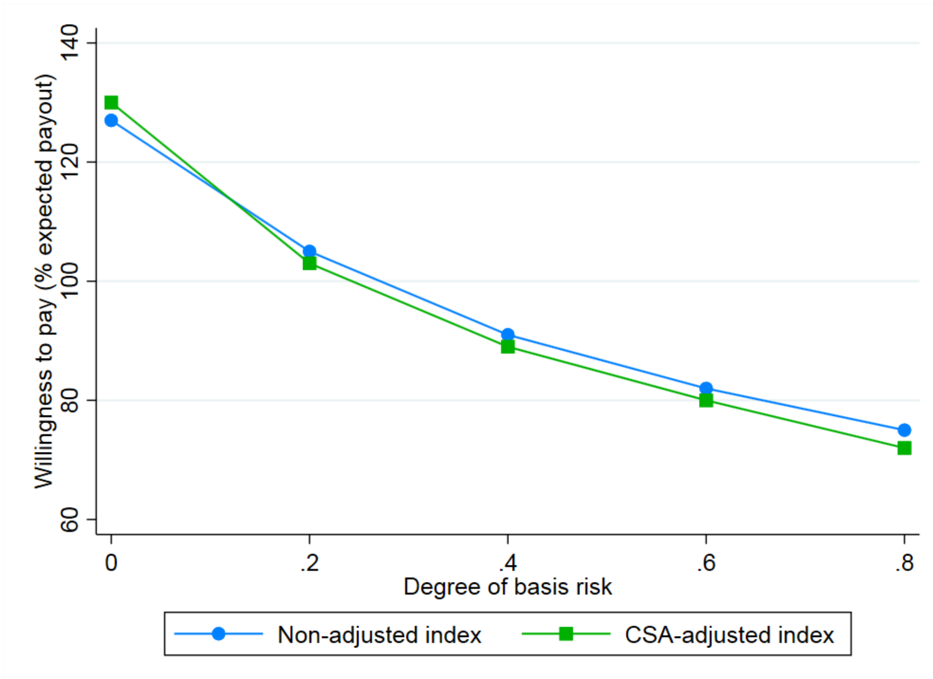
whereby $I = \tilde{Y} - Y_\zeta^\Lambda$ and $\mathrm{E}[I] = \tilde{Y} - \mathrm{E}Y_\zeta^\Lambda$. Inserting this into the equation above defines α_0^* and α_1^*, the maximum willingness to pay for the insurance policy calibrated to match payoffs under normal practices and CSA practices, respectively:

$$\mathrm{E}U(Y_\theta^1 + \tilde{Y} - Y_\zeta^0 - \alpha_0^*(\tilde{Y} - \mathrm{E}Y_\zeta^0)) = \mathrm{E}U(Y_\theta^1 + \tilde{Y} - Y_\zeta^1 - \alpha_1^*(\tilde{Y} - \mathrm{E}Y_\zeta^1)) = \mathrm{E}U(Y_\theta^1).$$

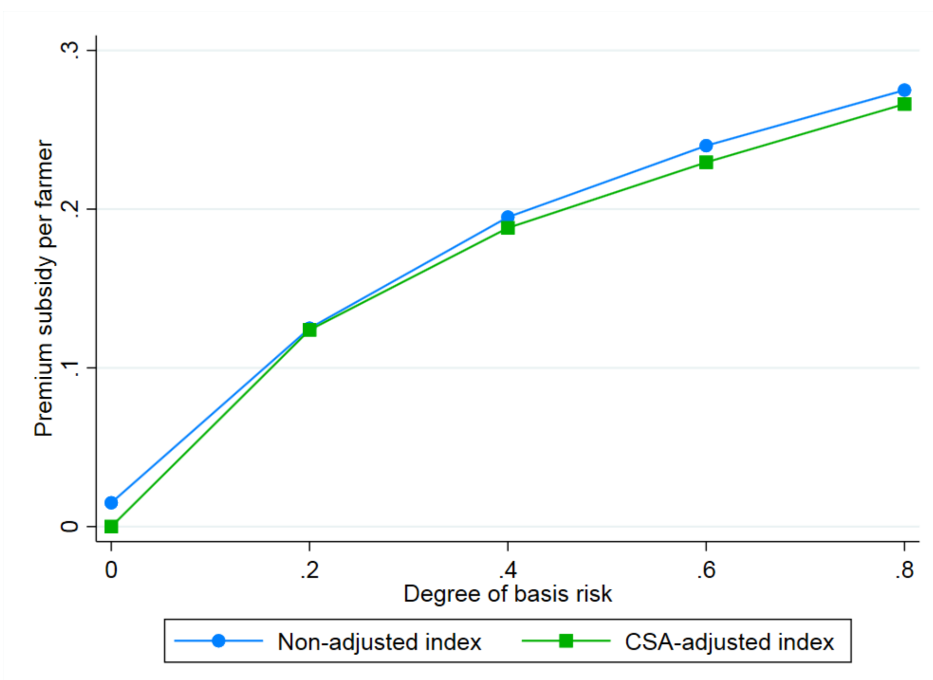
Figure 2 plots the demand for insurance by type of insurance product: the blue line with circle markers represents demand for the non-adjusted index, which triggers at the normal strike value, θ^0, whereas the green line with square markers represents demand for the bundled product with an adjusted index, which triggers at the CSA strike value, θ^1. In Panel (a), we refer to demand as the maximum proportion of expected insurance payouts (which would be the actuarially fair premium) that a farmer is willing to pay, α_Λ^*. On the horizontal axis, we vary the degree of basis risk. We model the weather shock to have a standard deviation of $\sigma = 1.2$ and we assume a constant relative risk aversion coefficient equal to $r = 1.6$. Income under optimal weather conditions is normalized to be $\tilde{Y} = 1$, the weather shock variables takes on values $\theta \in [0,4]$ and threshold θ^i is determined as $\theta^i = 1 + i$.

In the absence of basis risk, farmers are willing to pay 127 percent of the actuarially fair premium for the normal insurance product. Adjusting the insurance product increases the willingness to pay to 130 percent. With an insurance mark-up of 30 percent, this would mean that adjusting the product would improve insurance uptake, suggesting that the CSA adjustment could make the product sustainable at non-subsidized premiums. However, when introducing basis risk, this finding hinges upon the assumption that there is no

Figure 2: Demand for non-adjusted versus adjusted index insurance without adoption cost



(a) Willingness to pay as percentage of actuarially fair premium



(b) Difference between insurance premium and willingness to pay

Notes: The degree of basis risk is one minus ρ, that is, one minus the correlation between the log of the actual shock, $\log \theta_t$, and of the assumed shock, $\log \zeta_t$. We further assumed the following parameters: $\sigma = 1.2$, $r = 1.6$, $\tilde{Y} = 1$, $(\theta_t, \zeta_t) \in [0,4]$ and $\theta^{\lambda} = \lambda + 1$.

basis risk. When introducing a small amount of basis risk, the willingness to pay for insurance drops to levels just above the actuarially fair premium rate, and at higher levels of basis risk, the willingness to pay reduces further. Moreover, at these levels of basis risk, the demand for the CSA-adjusted product is lower than the demand for the non-adjusted product.

The finding above applies to the willingness to pay as a proportion of expected payouts. We standardize demand in that way, because expected payouts of the non-adjusted product are higher than those of the adjusted product. The willingness to pay for the non-adjusted product would be even higher compared to the adjusted product in absolute terms. However, at the same time, one could imagine a policymaker with the objective to maximize insurance take-up at minimal public spending. To boost insurance take-up, the policymaker could subsidize insurance premiums, and the question is how the policymaker could minimize these premiums.

Panel (b) of Figure 2 therefore plots the amount that a policymaker would need to subsidize in order to enhance uptake; that is, the difference between the insurance premium (set to 130 percent of expected payouts) and the amount that a farmer is willing to pay for insurance. When there is no basis risk, the policymaker is able to reduce premium subsidies by adjusting the index, and the savings in the subsidies required to maximize take-up appears to be increasing in basis risk. However, the savings from adjusting the index are dwarfed by the savings that could be accomplished by minimizing basis risk. Basis risk leads to such a large reduction in demand that innovations to help reduce basis risk could well lead to higher cost savings and improved welfare than CSA adjustments.

In a next iteration of the paper, we will also discuss the effects of bundling index insurance on CSA adoption at different levels of the insurance premium by adjusting α. We will then also discuss the effects of bundling indemnity insurance by explicitly conditioning insurance payouts on CSA technology adoption. We will analyze the effects on both the demand for such insurance products and the willingness to pay for the CSA technology by studying the effects of such explicit bundling on β.

3 Effects of bundling insurance with CSA: Evidence

In this section, we estimate the empirical effect of conditioning indemnity insurance coverage on CSA adoption, using an experiment conducted with wheat farmers from Haryana and Punjab, two states in northwest India, during the 2016/2017 winter (Rabi) season. The experiment aimed at identifying strategies to reduce agricultural residue burning in the period that farmers prepare their land for wheat production. Residue burning is considered a problematic activity in the region. CSA technologies in the form of conservation agriculture offer farmers with an alternative, as it allows farmers to leave the residues from their rice harvest on the field, and sow directly into the mulch or residues, without tilling the land before land preparation.

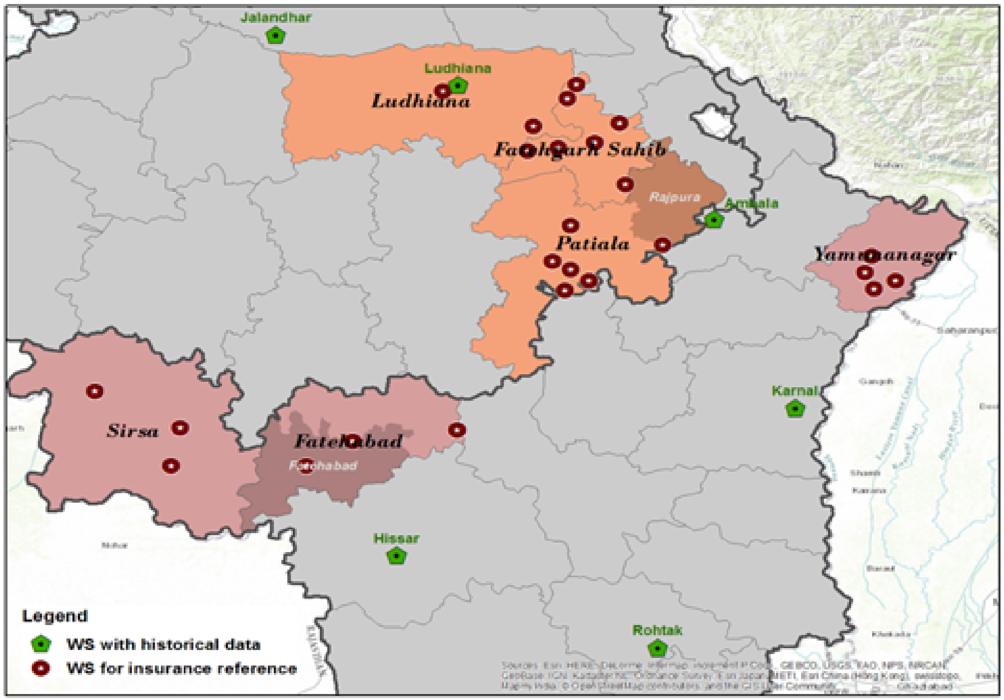
3.1 Study context: CSA and crop insurance in Haryana and Punjab

The study was conducted with wheat farmers from six districts in Haryana and Punjab, two states in northwest India (Figure 3). These two states are the second and third largest wheat producing states in India and the largest contributors to the central pool of food grains used to provide welfare entitlements to Indias poor. Having received major investment as the prime location for Indias "green revolution" in the 1960s, the two states have a high proportion of total cropped area under irrigation, with 99 percent in Punjab and 84 percent in Haryana, and a high use of fertilizers and mechanization compared to the rest of India. Farmers in these states also have higher agricultural incomes and larger landholding sizes compared to the rest of India.[5]

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

[5] Source: Government of India, 2016.

Figure 3: Map of study region



Moreover, farmers have struggled in the last decade with stagnating yield-growth and poor soil fertility.[6]

Farmers need financial instruments to cope with the hardship from these natural disasters, including bank accounts, credit, and insurance. Most farmers in the region have access to banking and credit through either cooperative societies or the Kisan Credit Card (KCC), a credit scheme for loans to promote investments in agricultural production. These financial instruments allow farmers to access savings and liquidity to cope with losses and smooth consumption in case of an income shock. However, the implicit insurance provided by these financial instruments is imperfect: in surveys conducted in the study area, around 70 percent of farmers said they have reduced large expenditures on items such as school fees and agricultural machinery to cope with weather shocks.

Insurance could potentially help farmers cope with shocks without having to reduce investments in education or agriculture. The Government of India therefore introduced in 2015/16 the Pradhan Mantri Fasal Bima Yojana (PMFBY, or Prime Ministers National Crop Insurance Scheme), a subsidized scheme to protect farmers against financial risks posed by extreme weather events. The PMFBY covers farmers for

[6] Source: Ministry of Agriculture and Farmers Welfare, 2015-2016.

prevented sowing, mid-season adversities, localized calamities due to hailstorms, inundation and unseasonal rains, but the main component is based on area-yield indices, meaning that payouts are triggered when the average yield measured through crop cutting experiments (CCEs) within a village drops below the historical average. The scheme is offered through voluntary enrolment; however, coverage is compulsory if a farmer takes out a loan through the KCC. Haryana decided to participate in the scheme.

Implementation of PMFBY has faced a multitude of challenges. Conducting CCEs is time-consuming and resource-intensive, creating a major cost and logistical burden for state governments and insurers. Unsurprisingly, this has led to long delays in processing CCE data and payments to farmers, and, in some states, failure to conduct CCEs altogether, resulting in major disputes about claim settlements. Indeed, in Haryana, according to the media, delays in payouts have been a persistent complaint about the insurance scheme, making the scheme unpopular.[7] Take-up was less than 10 percent of farming households in Kharif 2016 (in part due to poor coverage of cooperative societies) and most uptake was compulsory as it was linked to farmers taking out KCC loans (Bhushan and Kumar, 2017).

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

Hence, there is ample room for government investments to improve insurance coverage of farmers in these two states, either directly, through subsidizing insurance premiums, or indirectly, by investing in infrastructure necessary to provide insurance, for instance technology to facilitate enrollment and improve awareness of the scheme, linking cadastral maps and land documents with geospatial land cover data to verify the area sown under different crops and varieties, as well as investments in weather data and big data analytics to reduce basis risk.

[7] See this Financial Express article from July 25, 2017.

Alternatively, investments could focus on providing additional value by bundling insurance with ex-ante risk mitigation strategies, for instance climate information services, which have been shown to improve average profits (Rosenzweig and Udry, 2014), stress-tolerant seed varieties, or conservation agriculture, a system of climate-smart agricultural practices that is currently being promoted in Haryana and Punjab and the main focus of this paper. Conservation agriculture, also sometimes called sustained intensification, involves a combination of laser land leveling, directly seeding rice instead of transplanting it into the field, not burning residues from the rice harvest but instead adding these nutrients into the soil by sowing the next crop rotation (wheat) directly into these residues, without tilling the land.

The idea behind these ex-ante risk mitigation strategies is that they do not reduce farmer payoffs in years with normal weather conditions, and that in years with moderate weather, payoffs are higher under conservation agriculture than under conventional practice. For instance, conservation agriculture reduces exposure to moderate weather risk by reducing production costs (especially costs incurred for irrigation, labor, and fertilizers), and by improving the resilience of the wheat crop to natural disasters such as excess rainfall, heavy winds that can cause lodging, and extreme heat.

3.2 Methods

We were interested in whether we could reduce residue burning by giving farmers indemnity-based insurance, conditional on the farmer not burning his residues from the previous season. As part of the experiment, we provided weather index-based insurance (WBI) free of charge to all farmers who were surveyed in our six study districts. In four of these six districts, excluding Sirsa and Yamunanagar in Haryana (where residue burning rates were already lower at baseline), we randomized, at the village level, whether farmers received add-on indemnity insurance coverage (in addition to their WBI coverage), and, in a subset of the villages with this add-on indemnity coverage, we randomized whether insurance payouts would be conditional on the farmer not having burnt his residues from the previous harvest.

In total, we surveyed 540 farmers from 36 villages within these four districts. Among these villages, 18 villages (270 farmers) were randomly assigned to receive WBI only, unconditional on residue burning (WBI). Thus, this is our control group. Of the 18 villages in the treatment group, we randomly assigned 6 villages (90 farmers) to receive both WBI and add-on indemnity coverage, unconditional on residue burning. We included these villages as a placebo group that had indemnity coverage but without no-burning condition. The remaining 12 villages (180 farmers) were randomly assigned to receive both WBI and add-on indemnity coverage, but with insurance payouts being subject to the no-burning condition. This is our main treatment group. By comparing the placebo and treatment villages, we establish the effect of the no-burning condition.[8]

All farmers received their insurance coverage during village sessions in September-October 2016, which is also when they were informed–in the treatment villages–of the no-burning condition. The WBI product included coverage for excess rainfall and above-normal temperatures, measured from a nearby weather station. In placebo and treatment villages, farmers received WBI plus indemnity coverage. Indemnity coverage was implemented by means of picture-based insurance (PBI), compansating farmers for visible damage as detected from the smartphone pictures of the insured crop. In all villages, farmers were informed that they received insurance coverage in return for sending in pictures of their insured plots on a regular basis, from sowing to harvest (see Ceballos and Kramer, 2017 for more information about the PBI procedures).

3.3 Data

In treatment villages, insurance payouts were conditional on farmers not burning the residues on their insured plot (henceforth referred to as cPBI). The idea was to use the pictures that farmers were taking of their insured plots to assess whether farmers had burnt their crop residues from the previous harvest. However, the smartphone application that enabled farmers to take the pictures was not available on time. Hence, we sent out project field staff to observe for insured plots, in both the control group and the treatment group, whether the farmer had burnt crop residues. We will use the data from these objective and independent spot checks instead of subjective self-reported data to assess the effect of providing indemnity coverage subject to a no-burning condition.

[8] The specific randomization procedure was as follows. In total, there were 18 weather stations from which the study could source data in the four districts where the experiment was conducted, and we had sampled two villages within five kilometers from each weather station. For each weather station, one village was randomly assigned to the control group, and the other village was assigned to either the placebo or the treatment group. We randomized at the weather station level whether this village would be placebo or treatment.

The analyses will also control for characteristics measured during a baseline survey in August 2016, prior to the village sessions in which farmers received their insurance products. Table 1 presents a number of variables that were measured at baseline, along with a comparison of these characteristics across the treatment arms. Columns (1)-(2) provide the mean and standard deviations of these characteristics for the control group, which only received WBI coverage. Column (3) presents the difference in means between the placebo group (receiving both WBI and PBI, i.e. 'PBI') and the control group. Column (5) presents the difference in means between the treatment group (receiving WBI and PBI conditional on not burning residues, i.e., 'cPBI') and the placebo group.[9]

The average farmer in the control group is 40 years old, and is part of a household with on average six household members. Given that only one district in the experiment (Fatehabad) was located in Haryana, the majority of farmers speaks Punjabi instead of Hindi or Haryanbi, and most of the Punjabis follow the Sikh religion. Around 88 percent of farmers are married, nearly half (40.6 percent) have completed tertiary education, and farmers are on average a member of one organization. We do not observe differences in demographic characteristics across the control and placebo group, and the only difference between the treatment group compared to the placebo group is that household sizes are on average slightly larger in the treatment group ($p < 0.10$).

The next set of characteristics provide insights on the extent to which farmers have access to finance. Nearly all farmers (98.9 percent) have a bank account, but only 22.6 percent can access credit through the Kisan Credit Card (KCC) scheme. Moreover, only 8.4 percent of farmers with KCC, or 1.9 percent of the full sample, reports having crop insurance through the KCC. Trust in financial institutions is also not very high, with 39.8 percent of farmers reporting to have trust in these institutions. On average, farmers earn per year Rs. 509,000, which is nearly US$ 8,000 at current exchange rates, from crop production, and 36.4 percent of their crop income comes from wheat. Crop production is their main source of income. In the selected districts, cotton production is low.

The final set of characteristics are related to the adoption of conservation agriculture. More than half of all farmers have ever used a laser land leveler, but only 13.4 percent has ever used zero tillage, and 9.6

[9] These differences, and standard errors in Columns (4) and (6), were estimated by regressing baseline characteristics on dummy indicators for whether the farmer received PBI coverage ('PBI') and whether coverage was subject to the no-burning condition ('cPBI'), controlling for weather station fixed effects and clustering standard errors at the village level.

percent has left their residues as a cover on the soil. Most farmers, 84.3 percent, burn their residues after harvest.[10] Conservation agriculture is also not very common among peers, given that 37.5 percent of farmers has seen others practicing it. Nearly half of all farmers consider themselves to be progressive, suggesting that they would be interested in trying out new technologies when offered the chance. Farmers expect that adopting CA reduces their production costs by Rs. 1,607 per acre, but at the same time, they expect yields to be reduced, even in years with extreme heat or heavy winds, when CA moderates soil temperatures and prevents lodging. The objective of the experiment was to condition free insurance coverage on not burning residues to help overcome these adoption costs.

A number of financial characteristics and CA adoption measures are not well balanced across treatment arms. Randomization did not have the intended effect to create balanced samples across treatment arms in part because the number of villages was small, and because only six villages were randomly assigned to the placebo group. We will control for any variables that are not well balanced across treatment arms in our regression analyses when estimating treatment effects.

3.4 Results

In Table 2, we present the results from the experiment with the no-burning condition. We estimate the effects of the no-burning condition in two ways. First, we estimate the following equation:

$$Burnt_{fvw} = \beta_w + PBI_{vw}\beta_1 + cPBI_{vw}\beta_2 + \mathbf{x}_{fvw}\beta_x + \varepsilon_{fvw} \tag{7}$$

whereby $Burnt_{fvw}$ is a dummy variable equal to one if and only if field staff observed stubbles from burning residues in the insured plot for farmer f from village v near weather station w and zero otherwise, α_w is a weather station fixed effect, PBI_{vw} is a dummy variable equal to one if and only if village v near weather station w received picture-based add-on coverage, $cPBI_{vw}$ is a dummy variable equal to one if and only if insurance coverage in this village was subject to a no-burning condition, $\mathbf{x}_{fvw}$ is a vector of control variables for the farmer, and ε_{fvw} is an error term, for which we assume clustering at the village level. We will estimate

[10] This number is likely an underestimate, given that residue burning is officially illegal and hence farmers may have been reluctant to admit that they burnt residues on their fields after harvest.

Table 1. Baseline characteristics compared across treatment arms

Variable	Control group (WBI)		Placebo (PBI) vs. WBI		Treatment (cPBI) vs. PBI	
	Mean	(s.d.)	Mean	(s.e.)	Mean	(s.e.)
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics						
Age	40.42	(12.06)	-2.793	(2.008)	0.100	(2.360)
Household size	6.054	(2.475)	-0.227	(0.274)	0.571	(0.318)*
Speaks Hindi	0.038	(0.192)	0.035	(0.024)	0.005	(0.041)
Speaks Punjabi	0.931	(0.254)	0.000	(0.000)	-0.079	(0.053)
Is Sikh	0.896	(0.306)	0.012	(0.008)	-0.051	(0.080)
Is married	0.881	(0.324)	-0.067	(0.035)*	0.010	(0.044)
Has tertiary education	0.406	(0.492)	-0.012	(0.029)	0.052	(0.055)
Number of organizations	0.981	(0.767)	-0.110	(0.076)	0.069	(0.100)
Financial characteristics						
Has bank account	0.989	(0.107)	-0.010	(0.014)	0.010	(0.016)
Has Kisan Credit Card	0.226	(0.419)	0.030	(0.050)	-0.091	(0.057)
Has crop insurance through KCC	0.019	(0.137)	0.008	(0.017)	0.014	(0.019)
Has trust in financial institutions	0.398	(0.491)	0.171	(0.045)***	-0.262	(0.057)***
Log income crop production	13.14	(0.584)	-0.268	(0.079)***	0.171	(0.111)
Crop income share from wheat	0.364	(0.107)	0.010	(0.019)	0.001	(0.021)
Income share from crop production	0.822	(0.154)	-0.029	(0.025)	0.022	(0.030)
Income quintile	3.257	(1.381)	-0.515	(0.118)***	0.392	(0.192)**
Share of production from cotton	0.019	(0.130)	-0.028	(0.022)	0.039	(0.024)
CA adoption						
Ever used laser land leveler	0.659	(0.475)	-0.017	(0.082)	-0.064	(0.095)
Ever used zero till with happy seeder	0.134	(0.341)	0.034	(0.037)	-0.138	(0.046)***
Ever left residue untouched on field	0.096	(0.295)	-0.036	(0.022)	-0.029	(0.034)
Every burnt residues after harvest	0.843	(0.365)	0.120	(0.044)**	-0.145	(0.053)**
Has seen others practicing CA	0.375	(0.485)	0.068	(0.052)	-0.143	(0.073)*
Is a progressive farmer	0.402	(0.491)	-0.045	(0.032)	-0.073	(0.056)
Perceived effect of CA on ...						
... production costs	-1.607	(13.85)	-0.199	(0.203)	1.268	(0.673)*
... income in a normal year	-2.057	(2.877)	-0.111	(0.207)	-0.037	(0.468)
... income in a year with extreme heat	-1.590	(2.970)	-0.095	(0.181)	-0.159	(0.394)
... income in a year with lodging	-1.069	(3.386)	-0.020	(0.234)	-0.210	(0.375)

Notes: Columns (3) and (5) present the coefficients estimated from a regression of the shown variable on dummies for PBI (equal to one if offered PBI insurance coverage) and cPBI (equal to one if insurance coverage was subject to a no-burning condition), respectively, controlling for weather station fixed effects and with standard errors (shown in parentheses in Columns (4) and (6)) clustered by village. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this model using ordinary least squares (OLS).

A second model that we estimate is motivated by the observation that not all farmers in the treatment group recalled the no-burning condition at endline. Not all farmers attended the village sessions, and farmers may not have remembered the condition, especially if they were not much interested in the insurance product to begin with. Indeed, in the cPBI treatment group, 73.2 percent of farmers recalled the no-burning condition, meaning that about one quarter were not aware. Moreover, farmers in the placebo and control group may have (incorrectly) assumed that there was some conditionality. Indeed, in WBI and PBI villages without condition, 27.7 percent of farmers indicated at endline that they thought there was a no-burning condition. This could attenuate the effects of the no-burning condition.

We therefore also use a two-stage least squares approach to estimate the effects of the condition on observed burning rates. To that end, we construct a variable 'Recalls' to indicate farmers who recalled the no-burning condition at endline, and we estimate in the first stage the following equation,

$$Recalls_{fvw} = \gamma_w + PBI_{vw}\gamma_1 + cPBI_{vw}\gamma_2 + \mathbf{x}_{fvw}\gamma_x + \varepsilon^1_{fvw} \tag{8}$$

and in the second stage, we include the predicted value from this first stage, $\widehat{Recalls}_{fvw}$, to estimate the effect of the no-burning condition for those individuals who recalled the no-burning condition at endline using the following equation:

$$Burnt_{fvw} = \beta_w + PBI_{vw}\beta_1 + \widehat{Recalls}_{fvw}\beta_2 + \mathbf{x}_{fvw}\beta_x + \varepsilon_{fvw}. \tag{9}$$

In Table 2, Columns (1) and (3) present the effect of the no-burning condition using the OLS estimators, whereas Columns (2) and (4) present the two-stage least squares estimator for the effect of a farmer recalling the no-burning condition, using village assignment to the no-burning condition as an instrument. Columns (1) and (2) include weather station fixed effects but do not control for other variables ($\mathbf{x}_{fvw}$), whereas Columns (3) and (4) control for a large set of demographic, financial and agricultural characteristics that were either imbalanced in Table 1 or have predictive power.

In Column (1), we observe a 5.7 percent increase in burning rates in villages randomly assigned to receive PBI coverage, which is not statistically significant. Conditional on receiving PBI, the no-burning condition reduces burning rates by ten percentage points, which is significant at the 10 percent level. Using

Table 2. Effect of no-burning condition on observed residue burning

	Dependent variable: Stubbles from burning observed on insured plot			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Receives picture-based indemnity coverage (PBI)	0.057	0.079	0.083*	0.114*
	(0.044)	(0.053)	(0.043)	(0.061)
Insurance coverage is subject to no-burning condition (cPBI)	-0.100*		-0.122**	
	(0.058)		(0.055)	
Recalls the no-burning condition (instrumented by cPBI)		-0.269*		-0.342*
		(0.162)		(0.178)
Controls			✓	✓
Observations	343	333	331	321
Mean dependent variable	0.913	0.913	0.909	0.910
R-squared	0.398	0.311	0.437	0.277

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

instrumental variables in Column (2), we find an even larger reduction–26.9 percentage points–among farmers who recalled the no-burning condition at endline. Thus, at first glance, the no-burning condition did help reduce burning rates.

In Columns (3) and (4), we control for potentially confounding characteristics that were imbalanced across treatment arms. Doing so increases the size of the estimated coefficients. In Column (3), we observe a 12.2 percentage point reduction in burning rates for treatment villages conditional on receiving indemnity insurance coverage, which is significant at the 5 percent level. In Column (4), recalling a no-burning condition as a consequence of our experiment is associated with a 34.2 percent reduction in burning rates.

It is important to stress that we observe these effects conditional on receiving indemnity add-on coverage for damage visible in a time-series of pictures taken from the insured plot. The no-burning condition also reduces burning rates compared with villages where no such indemnity insurance coverage was offered, but the differences are not statistically significant. Moreover, note that observed burning rates were on average above 90 percent. This means that stubbles from burning were observed on the vast majority of farmers' plots, even in the treatment group, resulting in them forgoing their insurance coverage.

Combined, this lends to the conclusion that when offering indemnity insurance coverage to reduce basis risk, it could be worth conditioning on the adoption of risk-mitigating practices to help overcome the costs of starting a new practice. However, it is important to put measures in place such that farmers who decide to not adopt can still access insurance, albeit at higher premium rates, and we provide no evidence supporting the conditioning of stand-alone index insurance products on the adoption of CSA technologies.

4 Discussion

In this section, we discuss why the intervention did not have larger effects. We will show that farmers may have been more pessimistic about the benefits of CSA than agronomic trials suggest due to a first-time adoption cost. Agronomic evidence from field trials shows indeed that conservation agriculture performs as well as conventional practice in years with normal weather, and that it improves payoffs compared with conventional practice in years with moderate weather conditions. Insurance and CSA practices therefore both serve to improve resilience, albeit in different ways. Farmers, however, do not perceive it to be that way. We asked a sample of 750 farmers during a survey in the six study districts to indicate how much they expected yields to be under normal practice, and under CA, in three alternative scenarios: years with normal weather conditions, years with extreme heat, and years with heavy winds resulting in lodging. We also asked how much they expected their production costs to be, and aggregated this into perceived profits associated with the two systems.

Table 3 presents farmer perceptions of CA benefits. Panel A indicates expected yields under three scenarios. In years with normal weather conditions, CA reduces perceived yields by 1.8 quintals of wheat, from 19.5 to 17.7 quintals (9.4 percent). In years with lodging or extreme heat, yields are on average about two quintals lower, but the difference between normal practice and CA is less pronounced: CA reduces expected yields by 0.98 quintals (5.8 percent) in case of years with heavy lodging, and 1.42 quintals (8.0 percent) in case of extreme heat. Panel B presents perceived costs under the two systems.[11] CA reduces not only yields but also production costs per acre: from 7,869 to 6,697 INR (Indian Rupees), or 14.9 percent. This is driven by perceived cost savings in land preparation, fertilizer applications and weeding. Despite

[11] We did not ask these questions by type of weather since production costs are generally born prior to the flowering stage, before damage from lodging or high temperatures occur.

these cost savings, we find that CA reduces payoffs under all three scenarios in Panel C; by 7.4 percent in a normal year, 1.8 percent in years with heavy winds and lodging, and 5.2 percent in years with extreme heat.

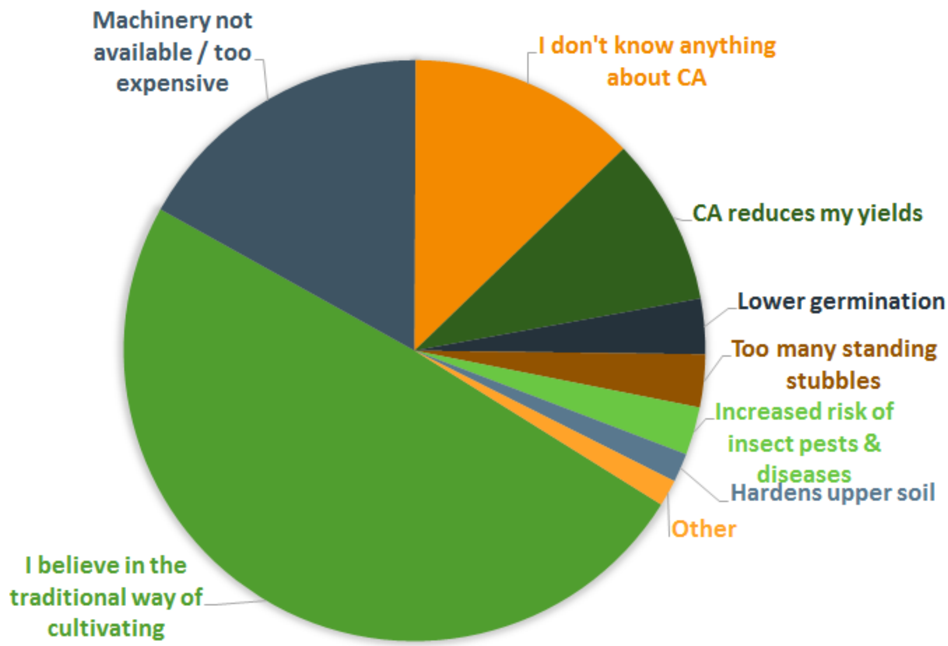
Table 3. Perceived yields and production costs: Normal practices versus conservation agriculture

	Normal practice (1)	Conservation agriculture (2)	Difference (3)
Panel A. Expected yields			
Normal year	19.50	17.67	1.832
Year with heavy winds/lodging	17.04	16.06	0.982
Year with extreme heat	17.72	16.30	1.419
Panel B. Perceived costs			
Land preparation	1608	457	1151
Sowing	713	1267	-554
Irrigation	282	242	40.5
Weeding	1159	947	212
Herbicides	649	722	-73.3
Fertilizers	2891	2483	408
Pesticides	567	580	-12.6
Total costs	7869	6697	1172
Panel C. Perceived payoffs (Expected yield*wheat price − production cost)			
Normal year	21872	20250	1622
Year with heavy winds/lodging	18125	17799	325
Year with extreme heat	19155	18162	993

Notes: Expected yields and profits are average values reported in a survey with 736 wheat farmers in Punjab and Haryana. To derive expected profits, we multiply the average expected yield level (in quintals per acre) with the median wheat price reported in the survey, which is Rs. 1525 per quintal (the minimum support price), and subtract the average level of expected production costs.

These stylized facts indicate that farmers are more pessimistic about the benefits from CA than agronomic trials suggest. Figure 4 shows potential explanations for why this is the case. When asked about the most important disadvantage of practicing CA, the majority of farmers report that they believe in the traditional way of cultivating wheat, followed by a large share of farmers indicating that they do not have (affordable) access to the right machinery to practice CA. Moreover, farmers report a lack of access to information on what CA is and how to practice it, and are concerned abuot reductions in yields. Hence, there appears to be an economic adoption cost in the form of investments in new machinery, training and experimentation, and a behavioral adoption cost of switching from default practices to a new technology.

Figure 4: Main disadvantage of conservation agriculture (CA)



5 Conclusion

This study analyzed the effects of bundling index insurance with CSA technologies. While insurance is suitable to cover losses from extreme or severe weather shocks, CSA technologies can help farmers reduce vulnerability from moderate weather shocks. We show that in theory, careful calibration of insurance indices to match payoff profiles under CSA technologies help improve the demand relative to the insured sum for insurance in a setting without basis risk. These findings do not necessarily generalize to an environment in which insurance products suffer from basis risk, due to an increased risk of suffering extreme income losses while the insurance index does not trigger. Moreover, the effects of reducing basis risk on the demand is significantly larger than the effects of bundling by itself.

The global insurance industry is nowadays making effort to minimize basis risk and to cover farmers for actual losses experienced. Doing so, products are moving closer towards indemnity insurance products with monitoring of agricultural practices and losses being facilitated increasingly through remote sensing and other technological innovations, such as picture-based insurance approaches. This raises the question how to bundle indemnity insurance with CSA technologies, and the present study offered one example of doing so. In a field experiment in northwest India, we find that conditioning insurance payouts from a free insurance product on not burning their residues enhanced residue management.

At the same time, we showed that many farmers decided to burn their residues. As a result, they lost their insurance coverage, since payouts were conditional on not burning the residues. We believe that a more inclusive approach would be to offer premium subsidies conditional on adopting CSA technologies, which could make the returns of not burning residues more salient. This could encourage farmers used to burning their agricultural residues to try out a new practice, bringing them closer towards a system of conservation agriculture practices. Other barriers to adoption were a lack of machinery and a lack of knowledge. Bundling insurance with these machinery services or credit to obtain the machinery, and bundling insurance with agricultural advisory or extension services could further help promote adoption. Identifying the complementarities of doing so are areas for future research.

References

Bhushan, C., Kumar, V., 2017. Pradhan mantri fasal bima yojana: An assessment. Tech. rep., Centre for Science and Environment, New Delhi.

Black, E., Greatrex, H., Young, M., Maidment, R., 2016a. Incorporating satellite data into weather index insurance. Bulletin of the American Meteorological Society 97 (10), ES203–ES206.

Black, E., Tarnavsky, E., Maidment, R., Greatrex, H., Mookerjee, A., Quaife, T., Brown, M., 2016b. The use of remotely sensed rainfall for managing drought risk: a case study of weather index insurance in zambia. Remote Sensing 8 (4), 342.

Carleton, T. A., 2017. Crop-damaging temperatures increase suicide rates in India. Proceedings of the National Academy of Sciences 114 (33), 87468751.

Carter, M. R., Cheng, L., Sarris, A., 2016. Where and how index insurance can boost the adoption of improved agricultural technologies. Journal of Development Economics 118, 59–71.

Ceballos, F., Kramer, B., 2017. The feasibility of picture-based crop insurance (PBI): Smartphone pictures for affordable crop insurance. Tech. rep., International Food Policy Research Institute (IFPRI).

Cole, S., Giné, X., Vickery, J., 2017. How does risk management influence production decisions? evidence from a field experiment. The Review of Financial Studies 30 (6), 1935–1970.

Hazell, P. B., 1992. The appropriate role of agricultural insurance in developing countries. Journal of International Development 4 (6), 567–581.

Hazell, P. B., Pomareda, C., Valdés, A., 1986. Crop insurance for agricultural development: Issues and experience. The Johns Hopkins University Press: Baltimore, Maryland.

Hobbs, P. R., 2007. Conservation agriculture: what is it and why is it important for future sustainable food production? The Journal of Agricultural Science 145 (2), 127.

Karlan, D., Osei, R., Osei-Akoto, I., Udry, C., 2014. Agricultural decisions after relaxing credit and risk constraints. The Quarterly Journal of Economics 129 (2), 597–652.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., et al., 2014. Climate-smart agriculture for food security. Nature Climate Change 4 (12), 1068–1072.

Lybbert, T., Carter, M. R., 2015. Bundling drought tolerance and index insurance to reduce rural household vulnerability to drought. In: Balisacan, A. M., Chakravorty, U., Ravago, M.-L. V. (Eds.), Sustainable Economic Development: Resources, Environment, and Institutions, Elsevier Academic Press, USA. Ch. 22, pp. 401–414.

Pandey, R., 2016. Groundwater irrigation in punjab: Some issues and a way forward. In: Economic Transformation of a Developing Economy. Springer, pp. 97–117.

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. Ch. 7, pp. 485–533.

Rosenzweig, M. R., Udry, C., 2014. Rainfall forecasts, weather, and wages over the agricultural production cycle. The American Economic Review: Papers and Proceedings 104 (5), 278–283.

Ward, P. S., Spielman, D. J., Ortega, D. L., Kumar, N., Minocha, S., 2015. Demand for complementary financial and technological tools for managing drought risk. IFPRI Discussion Paper 1430.