Money (Not) to Burn: Payments for Ecosystem Services to Reduce Crop Residue Burning*

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Abstract

We test whether payments for ecosystem services (PES) can curb the highly polluting practice of crop residue burning in India. Standard PES contracts pay participants after verification that they met a pro-environment condition (clearing fields without burning). We randomize paying a portion of the money upfront and unconditionally to address liquidity constraints and farmer distrust, which may undermine the standard contract's effectiveness. Incorporating contracts with partial upfront payment increases compliance by 10 percentage points, which is corroborated by satellite-based burning measurements. The cost per life saved is \$3600 to \$5400. The standard PES contract has no effect on burning.

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1 Introduction

Poor air quality is a leading preventable cause of mortality and illness globally (Fuller et al., 2022). In North India, air pollution reduces life expectancy by six to nine years for the region's half a billion residents, representing one of the world's largest pollution-related health burdens (Ghude et al., 2016; Lee and Greenstone, 2021). Agricultural fires are a major source of this pollution. Every winter, farmers burn rice stalk (residue) to clear their fields after harvest. Smoke blankets the region and drifts downwind to New Delhi, accounting for 30-40% of the city's winter air pollution (Bikkina et al., 2019; Govardhan et al., 2023).[1]

Crop residue burning is a classic example of an environmental externality, and the Indian government has responded with a command-and-control approach: Since 2015, burning residue has been banned and punishable by fines. However, the externality's inter-jurisdictional nature and a powerful farmer lobby have undermined political incentives to enforce the ban (Dipoppa and Gulzar, 2022). The government also introduced subsidies for farm equipment that removes residue without burning. However, subsidy levels are insufficient to cover the full cost of equipment use, and are restricted to certain equipment. With the existing policy mix, crop residue burning remains widespread (Aryal et al., 2023).

In this paper, we test whether payments for ecosystem services (PES) contracts, which condition cash transfers on avoiding an environmentally harmful behavior, can solve this problem. Like fines and subsidies for alternatives, compensating farmers for not burning residue increases their private cost of burning. PES, unlike fines, does not make potential polluters worse off. Unlike equipment subsidies, PES is agnostic about how the participant achieves the desired outcome; it targets the outcome rather than specific inputs. These features make PES a potentially attractive solution in settings where bans are poorly enforced, policymakers worry about impoverishing small landowners, and farmers' preferred alternatives are not well understood.

Contextual and institutional features common in lower-income countries motivate PES but can also restrict its efficacy, and that of conditional cash transfers more generally. Before receiving payment, PES participants must undertake the costly action required under the

[1] Crop residue burning is also an important pollution source in China (Chen et al., 2017), Southeast Asia (Oanh et al., 2018), and Africa (Cassou, 2018).

contract. They might not comply if they doubt the payment will be made or if they lack the cash needed to change behavior (e.g., to rent farm equipment to avoid burning). PES contracts that offer partial upfront payment may ease these constraints. An upfront payment sends a costly signal, increasing trust that the conditional payment will occur. It also provides liquidity to pay for the costs to comply.

We conducted a randomized controlled trial in 171 Punjabi villages during the 2019 rice growing season to assess the efficacy of standard PES versus PES with a partial upfront payment. Villages were randomized into three groups: no contracts (control), contracts with payment conditional on verification that the farmer did not burn (standard PES), and contracts that gave part of the payment to the farmer upfront and unconditionally, with the remainder paid conditionally after verification (upfront PES).[2]

Our main finding is that, despite smaller conditional payments, upfront PES had 10 percentage points (pp) higher contract compliance than standard PES. Remote sensing measures of burning confirm this result and, importantly, highlight the inframarginality of PES compliance under the standard contract. Specifically, farmers offered upfront PES burn 7.7 to 11.5 pp less than the control group. In contrast, standard PES had no effect on burning compared to the control group; farmers who complied in this arm would not have burned even if PES had not been offered. Consistent with the compliance and burning results, farmers in the upfront PES arm were 9.5 pp more likely than those in the control group to report removing crop residue with balers, while farmers in the standard PES arm reported no increase in the use of balers or other residue management equipment. Our findings indicate that appropriately designed incentive contracts, particularly those with an upfront payment component, can help policymakers make headway on this critical but difficult problem.

While upfront contracts are more effective at reducing burning, farmers receive upfront payments regardless of compliance, making them potentially less *cost*-effective than standard PES contracts. We calculate the cost per additional unburned acre and find upfront PES is at least as cost-effective as standard PES. Upfront PES costs ₹2,695 ($34) to ₹4,050 ($51) per averted acre of burning, less than the analogous (noisy) estimate for standard PES.[3]

[2] Our design has subtreatments that vary specifics of the standard or upfront PES contract, but our primary empirical specification pools subtreatments, as specified in our pre-analysis plan.

[3] Despite insignificant effects on burning, cost-effectiveness for standard PES is still well-defined using the

Our study contributes to the literature on PES by comparing alternative contract structures and, more specifically, by testing a novel contract design aimed at addressing institutional constraints and market failures that are common in lower-income countries and may limit the effectiveness of standard PES contracts. While some prior studies compare PES to a no-PES counterfactual (Jayachandran et al., 2017), and others have discussed the importance of careful PES design (Wunder et al., 2008; Engel et al., 2008; Jack, 2013; Kaczan et al., 2017; Oliva et al., 2020), we are unaware of prior work comparing PES contract structures. Furthermore, whereas most previous research focuses on PES to avert land use change (e.g., deforestation), we join a small set of studies applying the concept to air pollution (Edwards et al., 2020; Kramer and Ceballos, 2018). We also contribute to the broader literature on conditional cash transfers, which are used to encourage a wide range of socially desirable activities beyond environmental protection. Several studies have tested the importance of payment conditionality or timing (Baird et al., 2011; Akresh et al., 2013; Attanasio et al., 2015; Adhvaryu et al., 2023). Our contribution is to test a hybrid contract that combines a conditional payment and an unconditional upfront transfer.[4]

2 Background and study design

2.1 Crop residue burning and policy responses

About 80% of the planted area in the North Indian state of Punjab is cultivated using an annual rice-wheat dual crop system. Rice is farmed in Kharif (June-October) and wheat in Rabi (November-April), with a short time window to transition between crops. The introduction of mechanized harvesting in the 1980s facilitated adoption of this crop system and also created a need to manage crop residue: mechanized rice harvesting leaves 8 to 12 inches of stalk, representing over 2.5 tonnes of residue per acre of rice (Jain et al., 2014). Controlled burning has emerged as the primary method for clearing crop residue.[5]

estimated coefficients and standard errors.

[4]Related research includes Casaburi and Willis (2018), who test payment timing in insurance contracts, and Aker and Jack (2023), who evaluate the impact of payment timing on agricultural technology take-up.

[5]Restrictions on groundwater use and rising wages have contributed to the growth of residue burning (Balwinder-Singh et al., 2019; Behrer, 2019; Garg et al., 2021).

Recognizing the detrimental environmental consequences of residue burning, a 2015 court judgement prohibited the practice and directed North Indian state governments to levy fines ranging from ₹2,500 to ₹15,000, based on farmers' landholdings (Bhuvaneshwari et al., 2019; National Green Tribunal, 2015). Agricultural lobby opposition and weak enforcement have hampered implementation of this penalty-based policy. In 2017, the central government announced a two-year, $144 million program for the states of Punjab, Haryana, and Uttar Pradesh to subsidize *in-situ* crop residue management (CRM) equipment like the Happy Seeder. *In-situ* equipment keeps residue on the plot and sows the next crop directly through the residue. The subsidy program did not cover *ex-situ* equipment that removes residue from the fields; such equipment includes balers which bundle and then remove residue from the plot.[6]

Despite this subsidy scheme, CRM equipment rental costs remain high. Farmers typically rent equipment via hiring centers or agricultural cooperatives, which receive an 80% subsidy on equipment purchases. According to our baseline survey, the median Happy Seeder rental cost was ₹1,250 per acre, with a total *in-situ* residue management cost of about ₹3,000 per acre. Farmers may prefer unsubsidized *ex-situ* methods because they are cheaper (e.g., renting a baler costs around ₹1,000 per acre) or are perceived as less damaging to yields.

Introducing a PES program effectively decreases the price of renting either *ex-situ* or *in-situ* equipment. However, the fact that PES payments occur after residue has been removed means that liquidity constraints can be a barrier to CRM equipment use. In addition, farmers may not trust that the payment will be made ex post as promised. At baseline, only 13% of farmers stated they entirely trusted the government, while only 7% trusted NGOs. Less than half had ₹5,000 in savings, and the majority identified acquiring a ₹5,000 loan as somewhat difficult or difficult. (A typical study farmer has 5 acres of rice production and would pay ₹15,000 to rent *in-situ* equipment and ₹5,000 to rent a baler.)

[6] Baled straw is often used as an industrial heat source. Nian (2023) finds that, in China, biomass power plants reduced residue burning.

2.2 PES contracts and randomization design

We offered treated farmers either standard or partial upfront payment PES contracts (58 and 62 villages, respectively). Each treatment had two subtreatments, which we pre-specified pooling for the main analyses.

Based on discussions with the Punjab government about a scalable payment level, we set our base standard PES contract, which pays out only once the absence of burning is verified, at ₹800 per acre. To assess the importance of payment amounts, we introduced another standard PES contract that pays twice as much, ₹1600 per acre.[7]

Our second treatment arm addressed trust and liquidity concerns by paying a portion upfront, and the rest contingent on verified non-burning. To match our base contract, the sum of the (potential) upfront and ex post payments was set at ₹800. The only difference between the two subtreatments was whether 25% or 50% was paid upfront. Figure A.1 summarizes the experimental design, which also includes a status quo control group (51 villages).[8] Figure A.2 depicts the timeline for data collection and agricultural activities.

While upfront payments, in principle, could be recouped from a non-compliant participant, doing so is challenging (e.g., because participants are poor). Our contract explicitly made the upfront payment unconditional, without increasing the total potential payment. This means that the conditional amount – the farmer's incentive to comply – is lower in the upfront contract, which could potentially result in lower compliance than with standard PES. Even if compliance increases, unconditional payments may lower PES cost-effectiveness since farmers who do not comply will still receive upfront payments. (Farmers' participation in all treatments was voluntary, with contract non-compliance only 'penalized' by non-payment of the conditional component.)

[7] In November 2019 (after our intervention), the federal court ordered the Punjab government to pay farmers ₹100 per quintal of paddy, or about ₹2,500 per acre, conditional on (self-reported) not burning. Concerns about the veracity of farmers' self-declarations that they did not burn led to the program's suspension a few weeks later. In our endline survey, about 30% of the sample was aware of the government program, and most of them reported learning about the program after having begun residue management.

[8] Randomization occurred concurrently with household listing and baseline surveys. We stratify on district, below/above median number of eligible households, and whether the baseline and listing survey were finished. A fifth strata of 15 villages was added after initial randomization.

2.3 Sampling and baseline survey

Bathinda and Faridkot in Punjab were chosen as study districts because they had high rates of burning and relatively few other organizations working to encourage CRM adoption. We identified the 300 villages with the most farmer cooperative members using membership lists, and then screened farmers for eligibility by phone in fall 2019. Farmers were eligible if they grew 2-12 acres of paddy, planned to harvest after the second week of October and plant a Rabi crop, and used farm equipment that was indicative of burning (specifically, a reaper or no chopper) the previous year. The last criterion means that our sample had higher burning than average; by minimizing inframarginal payments through sample design, we increased statistical power to detect changes.[9]

We conducted a baseline survey in October 2019, prioritizing villages based on the number of eligible households. Baseline data collection ended when the target sample of 176 villages was reached. Enumerators moved down a randomly ordered list of cooperative members within a village, surveying the identified person on the list until 16 surveys were completed or the list was exhausted. Villages with fewer than six completed baseline surveys were excluded, resulting in a final sample of 171 villages and 1,668 respondents.

In over 90% of households, the person surveyed made household agricultural decisions. We collected data on demographics, agricultural production, income and credit constraints, trust in organizations, and barriers to CRM use. Over half of study farmers' household income is from agriculture, with a control group mean agricultural profit of ₹114,000 (median: ₹58,000). Roughly half (48%) had ever signed a written contract. As per our pre-analysis plan, we construct distrust and financial constraints indices from baseline data. We also construct CRM equipment access indices; access might affect PES compliance but to a similar degree in standard and upfront PES (see Appendix A.4 for survey questions used for indices). In the survey, farmers listed all paddy plots and accompanied the enumerator to collect geocoded plot perimeter measurements. Plot perimeters formed the basis for monitoring farmers' contract compliance and for linking satellite imagery to plots.[10]

[9] Table A.1 compares eligible farmers to all farmers, based on a census of four study villages.

[10] Because plots were measured before treatment assignment, measurement error should be orthogonal to treatment. We drop 47 plots (1.6%) where the plot ID was missing from the geospatial data or two plots completely overlap.

2.4 Contract implementation

J-PAL enumerators offered eligible farmers in treatment villages a PES contract, typically within a week of the baseline survey. The enumerator read the contract provisions to interested farmers (Appendix A.3 shows a sample contract). Enumerators recorded whether the farmer was offered the PES contract, reasons for not offering it (e.g., farmer could not be found or lacked a bank account), and whether he accepted.[11] Farmers who took up the contract received a handout detailing contract terms and burning verification procedures. Their entire paddy acreage (as measured during the baseline survey) was enrolled. The contract capped the maximum farmer payment at ₹16,000 in the ₹1,600 per acre arm and ₹8,000 in other treatment arms.[12] Farmers in the upfront PES arm received bank deposits 2-3 days after take-up.

Contract monitoring and enforcement required verifying that paddy plots were not burned. Visual inspection post-harvest and before tilling can ascertain whether or not a plot was burned. Monitoring too early, before residue management is completed, cannot rule out future burning; monitoring too late, post-tilling, might miss signs of burning. Since the project staff had to monitor the plot within a farmer-specific window of a few days, the farmer was made responsible for contacting J-PAL after residue management and at least four days before Rabi tilling.[13] Placing this onus on the farmer might lower contract compliance, but was necessary for accurate, affordable monitoring. Field staff then visited and inspected each plot, walking onto it, inspecting the soil, and checking the perimeter. They recorded several specific observations, such as the presence of burned straw, grey or black ash on the soil, and burned roots, grass, weeds, or tree branches at the plot boundaries. Outcomes across plots were aggregated into a single farmer-level compliance metric — any burning was a contract violation. Compliant farmers were paid within 2-3 days of monitoring.

[11] Contract payments were electronic, with bank account information only collected from treatment farmers. Only six farmers were screened out for lack of a bank account.

[12] For the 7% of farmers cultivating >10 acres of paddy (eligibility required ≤12 acres), the (potential) payment is constrained by the cap.

[13] Farmers who had not yet requested monitoring were reminded in late October to do so. Up to two monitoring visits could be requested to accommodate separate plots having different planting schedules.

2.5 Outcome data

Contract take-up and compliance Contract take-up was recorded at the time of the contract offer. Compliance is an indicator for whether a farmer requested monitoring and all his plots were assessed as harvested and unburned during the monitoring visits.

Remote sensing measures Contract compliance is uninformative about unmonitored farmers' burning. Some control group farmers and some treatment group farmers who did not enroll or request monitoring may not have burned. Following our pre-analysis plan, our primary outcome is a satellite-based burning measure constructed for all study farmers.

We train a random forest (RF) model using validated (ground) data and high-resolution satellite imagery for a subset of plots. Our validated data comprises monitoring data for treatment farmers and data from spot checks conducted on one randomly selected plot for 50% of farmers per village in November 2019. Spot checks and monitoring visits followed similar protocols; however, unlike monitoring visits, spot checks could not be synchronized with the farmer's residue management timing.[14] The satellite imagery comes from two complementary sources, PlanetScope and Sentinel-2.[15] The higher frequency PlanetScope data (roughly every 2-3 days) is less likely to miss burning events. This is important because burned plots become observationally similar to unburned plots once the soil is tilled for Rabi planting (see Figure A.3 for an example). Sentinel-2 data (every week to 10 days) also covers the mid-infrared range, which helps distinguish burned and unburned plots.

Our labeled set of 681 plots include burn labels (positives) from both the spot checks and the monitoring data and no-burn labels (negatives) from only the monitoring data.[16] We train the RF model using these labeled data (burn or no-burn) and pixel-level data from the two sensors.

The RF model outputs a pixel-level continuous score ranging from 0 to 1, representing

[14]Another difference is that observations occurred without walking onto the plot. We do not use spot check data as a primary outcome because sufficient statistical power would have required repeated visits, which might have directly affected behavior.

[15]PlanetScope has 3-meter resolution and Sentinel, 20-meter. Other commonly used sensors (MODIS and VIIRS) have lower resolution, 375 meters to 1 kilometer, which is too coarse for the small plots in our study.

[16]We exclude negative labels from spot checks because they indicate no burning in days immediately preceding the spot check visit but provide no information about burning outside that window. Appendix A.5 finds no indication of bias from the lack of negative labels in the control group.

the proportion of decision trees per pixel classified as burned by the model. To aggregate pixel-level scores to a plot-level burning outcome, we average the score across pixels in a plot (omitting perimeter pixels), and select the plot-level classification threshold (above which a plot in the training data is classified as burned) that maximizes overall prediction accuracy relative to the plot-level label. To avoid model over-fitting, we hold out each (multi-pixel) plot from the training set and obtain a prediction for the held-out pixels (Leave-One-Out Cross-Validation). The trained models are averaged and applied to both labeled and unlabeled plots. Specifically, we use the trained pixel-level RF model to predict pixel-level outcomes, then apply the classification threshold from the training set to aggregate up to the plot level. This procedure produces our primary 'maximum accuracy' outcome measure, which has 82% accuracy. Since the maximum accuracy classification predicts burn outcomes more accurately than no-burn outcomes, we provide a robustness check using an alternative classification threshold that balances the accuracy of predicting burning and non-burning in the training data. This 'balanced accuracy' outcome measure has 78% accuracy. Appendix A.5 and Walker et al. (2022) provide additional detail on the data, data processing, and machine learning model.

When assessing treatment effects, we invert the burning classification to obtain an 'unburned' measure that is directionally consistent with other contract outcomes (such that a higher value is an environmental improvement). If a farmer is predicted to have burned any of his plots, the farmer-level unburned outcome equals zero.

Endline survey We conducted a phone-based endline survey in June 2020, after Rabi harvest. We collected information about baler (*ex-situ*) and Happy Seeder (*in-situ*) use, the importance of cash and trust in decisions about burning the previous fall, and agricultural outcomes.

2.6 Experimental validity

We report four balance tests: pooled treatment arms versus control group, standard PES versus control group, upfront PES versus control group, and upfront PES versus standard PES (see Table A.2). The p-value of the joint F-test is 0.48 between treatment and control and 0.81 between standard and upfront PES. Self-reported burning in 2018 is balanced in each comparison. We observe slight imbalance for land size and CRM indices in some tests.

Our PES compliance and remotely-sensed burning outcomes have no attrition. In the endline survey, which had 17% attrition overall, the treatment group response rate was 5 pp lower than the control group, while the standard and upfront PES response rates were similar (see Table A.3). Table A.4 shows that this endline attrition does not vary systematically with baseline characteristics. For analyses using endline survey data, we show robustness to using Lee bounds (Lee, 2009).

3 Results

We estimate the following equation:

$$y_{ij} = \alpha + \beta StandardPES_j + \gamma UpfrontPES_j + \psi X_j + \epsilon_{ij} \quad (1)$$

where y_{ij} denotes an outcome for farmer i in village j, and $StandardPES_j$ and $UpfrontPES_j$ are indicator variables for village j assignment to standard PES and upfront PES treatments, respectively. X_j are strata fixed effects. Following our pre-analysis plan, and to increase statistical power, we pool treatment variants (different payment levels in $StandardPES_j$ and different proportions paid upfront in $UpfrontPES_j$). Standard errors are clustered at the village level. β and γ capture the effects of being assigned to the standard PES treatment and upfront PES treatment, respectively (relative to the control group).

3.1 Did farmers take up PES contract offers?

Figure 1 reports three treatment effects. We first show whether the farmer was found during the contract offer visit and whether he was eligible for and offered the contract (had a bank account and had not yet harvested his paddy). These outcomes are zero by construction in the control group, and are determined for treatment farmers before they learned their contract type. We observe no differences in these outcomes between the standard and upfront PES arms.

The third outcome shown in Figure 1 is program take-up (whether a farmer signed the PES contract), which is also zero by construction for control farmers. In both treatment arms, take-up was high, at 72%.[17] Conditional on being found and eligible, the contract take-up rate was 87%. This is consistent with the contract's high option value in both treatments, because farmers who choose to burn forgo the conditional payments but incur no penalties. The lack of additional take-up in the upfront PES arm may reflect trust concerns that were not resolved through upfront payments, such as objections to sharing bank account information, or the 2-3 day lag between signing and receiving upfront cash.

3.2 Did PES treatment farmers reduce crop residue burning?

Table 1, column (1), examines treatment impacts on contract compliance, i.e., if the farmer requested monitoring and no plots were recorded as burned during the monitoring visit(s). In the standard PES group, 8.5% of farmers complied. Compliance in the upfront arm is 10 pp higher, at 18%. Equality between the two groups can be rejected with $p < 0.01$.[18] Thus, upfront payments make farmers twice as likely to comply with the contract.

Next, we analyze remote sensing measures of whether a farmer burned any plots. Column (2) uses our main outcome and shows that, relative to the control group, upfront PES increases the likelihood that a farmer did not burn by 7.7 pp, or 85%, relative to the control group. The modest effect size in absolute terms (most farmers still burned) suggests that most farmers' full (opportunity) cost of alternatives to burning was higher than the payment level.

Unlike the estimate for upfront PES, the effect of standard PES relative to the control group is indistinguishable from zero. Thus, standard PES payments were entirely infra-marginal: farmers who complied with the standard PES contract would not have burned their plots even in the absence of the program. The p-value for the comparison of the effect on burning for upfront versus standard PES is 0.07. In column (3) we report results using the alternative balanced accuracy measure and see that upfront PES reduces burning by

[17] Table A.6 shows similar take-up rates across all sub-treatments.

[18] Treatment effects on whether the farmer requested monitoring (regardless of compliance) follow a similar pattern; 11% of farmers in standard PES requested monitoring versus 21% in the upfront arm.

11.5 pp relative to the control group and 9.8 pp relative to standard PES (p-value < 0.001).

While the effect sizes for the two remote sensing measures – based on different classification thresholds – are broadly similar (7.7 and 11.5 pp for upfront PES relative to control), Figure A.4 further explores sensitivity of the effect sizes to the threshold for classifying burning. As the threshold increases, pixels and plots are more likely to be relabeled as burned, so the control mean for being unburned decreases, and this mechanically decreases the estimated treatment effects. For upfront PES, the treatment effect is always statistically significantly positive except at the most extreme threshold. Standard PES never has a statistically significant effect. Table A.5 shows additional robustness checks. First, we report plot-level analysis; 18% of farmers had at least one plot predicted to be burned and also at least one plot predicted to be unburned. Plot-level treatment effects are of similar magnitude to our main farmer-level result. Second, treatment effects estimated on spot check data are also similar in magnitude, but with considerably lower statistical power and an unburned rate in the control group that is mechanically higher because the one-time plot visit missed some burns.

Though we lack statistical power to test for arm-by-arm differences, we describe the effects of each of the four sub-treatments briefly (see Table A.6). Paying more in the standard PES contract (₹1,600 versus ₹800) results in statistically insignificant increases in compliance and non-burning. Compliance is lower in the ₹1,600 arm than in either upfront PES arm. This is striking given that the upfront contract only pays ₹800 per acre. It is theoretically ambiguous which of the two upfront arms (25% upfront versus 50% upfront) should perform better; increasing the fraction paid upfront meant a lower reward for compliance. We find similar effects for the two variants, with slightly larger but statistically indistinguishable impacts when 50% is paid upfront.

In columns (4) and (5) of Table 1, we report treatment effects on the main *ex-situ* and *in-situ* alternatives to burning: self-reported baler and Happy Seeder use. Increased baler usage – by 10 pp – can explain all of the reduced burning achieved through upfront PES; every farmer who switched away from burning due to upfront PES seems to have switched to baling their straw. (The lower and upper Lee bound point estimates are 8.8 and 14.5 pp; see Table A.7). There are no detectable changes in Happy Seeder use in the upfront arm.

Consistent with the null effect of standard PES on our remote-sensing burning measures, we see no difference in baler or Happy Seeder usage in the standard PES arm relative to the control group.[19]

3.3 Why did upfront PES increase compliance?

Upfront PES reduces burning more than standard PES. We hypothesize that two mechanisms, distrust in the conditional payment and limited cash-on-hand to rent CRM equipment, may be important for explaining this result. Following our pre-analysis plan, we test for heterogeneous treatment effects based on baseline indices for each mechanism.[20] In Table 2 Panel A, we find that upfront PES performed no better than standard PES for farmers with high liquidity constraints or high distrust.[21]

In the endline survey, we asked a subset (63%) of farmers in both treatment arms about trust in the PES program and financial constraints influencing their CRM decisions.[22] Farmers in the upfront arm were 7 pp more likely than farmers in the standard PES arm to say they trusted that the conditional payment would be made if they complied (see Table 2).[23] In contrast, farmers in the upfront and standard PES arms did not differ in how important they said cash shortages were in their CRM decision-making. This does not necessarily imply that upfront payments are unimportant for easing liquidity constraints and enabling CRM equipment use, as the upfront amount (which could cover less than half the cost of baler rental) may have been too low to meaningfully ease this constraint for most farmers.

[19]Besides lower costs, farmers cite less delay in sowing the Rabi crop and higher agricultural yields as benefits of burning. We test for these effects in Table A.8. The average effects are statistically insignificant, but the confidence intervals and Lee bounds are wide..

[20]Table A.10 presents additional pre-specified heterogeneous treatment effects that pertain to the overall effect of PES. Farmers with greater information constraints and more negative beliefs about burning alternatives are less likely to comply with PES, pooling the treatment arms. Table A.9 also tests whether program take-up is differential by five pre-specified indices (liquidity, distrust, information about CRM alternatives, CRM access constraints, and negative beliefs about burning alternatives).

[21]This null result, like any heterogeneity on observables, may indicate that the measures are bad proxies for the construct, are correlated with other factors, or have limited variation in our sample.

[22]We only asked these questions to a subset of farmers because, due to respondent fatigue with a lengthy phone survey, we reduced the survey duration halfway through the sample.

[23] Trust in the conditional payment is higher in upfront PES for both compliant and non-compliant farmers. Thus, trust appears to increase with receipt of the upfront payment rather than the conditional payment. In contrast, in the standard PES arm, trust in the ex-post payment depends on whether the farmer received it (i.e., whether he complied). At the same time, high levels of trust in all arms means that variation in trust cannot fully explain the treatment effects.

4 Program costs and benefits

Although upfront PES is more effective than standard PES at reducing burning, relative cost-effectiveness is ambiguous because upfront payments are made regardless of compliance. The top panel of Figure 2 shows that treatment effects on contract payments per acre of rice cultivation (zero by construction in the control group) are higher in upfront PES due to higher compliance and to upfront payments being made to all farmers who took up.

To assess cost-effectiveness, we estimate the cost per additional unburned acre by dividing costs per acre cultivated from the top panel of Figure 2 by the treatment effect on the remote sensing outcome measure reported in Table 1.[24] The effect of standard PES on non-burning is small and statistically imprecise, which makes cost-effectiveness comparisons across arms highly imprecise. Specifically, using our main remote sensing model (maximum accuracy), upfront PES costs ₹4050 ($51) per unburned acre, compared to ₹5157 ($64) for standard PES (bottom left panel of Figure 2). With the alternative balanced accuracy model, upfront PES costs ₹2695 per unburned acre, compared to ₹13,441 for standard PES (bottom right panel). Even with this stark difference in point estimates, the lack of precision when comparing the estimates makes it hard to draw policy conclusions. Accordingly, we conduct the cost-benefit calculation using results from the upfront arm only.[25]

We benchmark these costs against a rough estimate of the averted-mortality benefits of reducing crop burning. Lan et al. (2022) combine satellite data on fire intensity with air transport models to estimate 86,000 premature deaths from crop residue burning in India in 2018, 43% of which can be attributed to Kharif burning in Punjab.[26] Estimates of the Value of a Statistical Life (VSL) for India range from around $688,000 (Majumder et al., 2018) to $5.6 million (Madheswaran, 2007). Using the lower bound of this range as a conservative estimate, this implies over $25 billion in annual damages from burning in Punjab. Kumar et al. (2019) estimates that around 4 million acres of Punjab's (non-basmati) paddy was burned in the Kharif season of 2018. Combining these assumptions, the lower bound of

[24] Monitoring costs are around ₹11 and 22 per acre in standard and upfront PES, respectively. Enrollment costs are ₹60 per acre in both arms. We omit these from our calculations because they are small and specific to our trial.

[25] Inputs to the cost-benefit calculations are provided in Appendix A.6.

[26] The impacts of pollution may be nonlinear, but a full accounting of marginal effects of burning for this back-of-the-envelope calculation is beyond the scope of the paper.

mortality damages of burning are about \$6,400 per acre (₹513,000), which is 125 to 190 times the per acre cost of reducing burning through PES with upfront payment. Put differently, the cost of upfront PES was \$3600 to \$5400 per life saved.

5 Conclusion

Incentive programs that reward people for socially desirable actions are an especially attractive approach in developing countries due to the economic and governance environment: The alternative of mandating the action, with punishment for non-compliance, risks economically harming the poor and can be unsuccessful when state capacity is limited. Our study design and findings highlight the importance of also factoring in these contextual realities when designing incentive programs. In particular, limited access to short-term capital and distrust in institutions can limit the effectiveness of standard PES contracts, as evidenced by better contract outcomes when some payment was offered upfront. This insight is likely to generalize to other PES programs where participants incur immediate costs to comply or distrust that the organization promising future payments will follow through. It also generalizes beyond PES to conditional cash transfer programs more broadly.

Besides distrust and cash constraints, the modest payment levels we used presumably lowered the impact of both the standard and upfront PES contracts. Our back-of-the-envelope estimate of mortality costs suggests that the benefits of eliminating crop residue burning are enormous. A scaled-up PES program could offer much more generous payment levels and still be cost-effective.

Scaling up the PES contracts we trialled would pose some new challenges. Our monitoring protocols were not designed for scale. Viable approaches to large-scale monitoring, such as remote sensing, are likely to increase contract risk because of measurement error (though different forms of contractual risks, such as corruption, may also exist with scaled-up in-person monitoring). In addition, equipment to manage crop residue is still scarce, and PES at scale would increase demand for this equipment, driving up rental prices unless supply constraints are addressed simultaneously.

There is also cause for optimism. A scaled-up PES program could be considerably more cost-effective than the one we evaluated, for several reasons. First, if trust is the main barrier to compliance, a smaller upfront payment might suffice to mitigate distrust. Second, higher overall payment levels would increase compliance, so fewer of the upfront payments would be to those who burn, decreasing payments per complier and improving cost-effectiveness. Third, dynamic incentives — in the form of tying future eligibility to verified non-burning — could reduce the payment level needed to achieve compliance and the likelihood that upfront payments go to those who continue to burn their residue. Fourth, the need for upfront payments might fade over time as trust in the program increases. Similarly, a longer-term PES program might stimulate the development of a market for short-term loans for equipment rental, addressing liquidity constraints and obviating the need for long-term upfront payments. Furthermore, the roll-out of a large-scale PES program would create incentives for innovation in better CRM equipment or rental market efficiency.

These benefits still leave the political challenge that, due to cross-jurisdiction externalities, cooperation across jurisdictions is needed for government implementation. Thus, a final attractive feature of PES programs is that they can be implemented by organizations that want to reduce fires but lack the authority to levy fines. The enormity of the environmental damages caused by crop residue burning in India justifies such an investment and also highlights the need for further research to find viable solutions to this problem.

References

Adhvaryu, A., J.-F. Gauthier, P. Jakiela, and D. Karlan (2023). Great expectations: Responses to current and future transfers for low-income individuals. *Working Paper*.

Aker, J. C. and B. K. Jack (2023). Harvesting the rain: The adoption of environmental technologies in the Sahel. *Review of Economics and Statistics Accepted*.

Akresh, R., D. De Walque, and H. Kazianga (2013). Cash transfers and child schooling: Evidence from a randomized evaluation of the role of conditionality. Policy Research Working Paper 6340, The World Bank.

Aryal, A., V. Lakshmi, B. W. Chenault, and S. Sekhri (2023). Bans without bite: Unabated stubble burning in india.

Attanasio, O. P., V. Oppedisano, and M. Vera-Hernández (2015). Should cash transfers be conditional? Conditionality, preventive care, and health outcomes. *American Economic Journal: Applied Economics 7*(2), 35–52.

Baird, S., C. McIntosh, and B. Özler (2011). Cash or condition? Evidence from a cash transfer experiment. *Quarterly Journal of Economics 126*(4), 1709–1753.

Balwinder-Singh, A. J. McDonald, A. K. Srivastava, and B. Gerard (2019). Tradeoffs between groundwater conservation and air pollution from agricultural fires in northwest india. *Nature Sustainability 2*(7), 580–583.

Behrer, A. P. (2019). Earth, wind and fire: The impact of anti-poverty efforts on Indian agriculture and air pollution. Working Paper.

Bhuvaneshwari, S., H. Hettiarachchi, and J. N. Meegoda (2019). Crop residue burning in India: Policy challenges and potential solutions. *International Journal of Environmental Research and Public Health 16*(5), 832.

Bikkina, S., A. Andersson, E. N. Kirillova, H. Holmstrand, S. Tiwari, A. K. Srivastava, D. S. Bisht, and Ö. Gustafsson (2019). Air quality in megacity delhi affected by countryside biomass burning. *Nature Sustainability 2*(3), 200–205.

Casaburi, L. and J. Willis (2018). Time versus state in insurance: Experimental evidence from contract farming in Kenya. *American Economic Review 108*(12), 3778–3813.

Cassou, E. (2018). Agricultural pollution: Field burning. *World Bank: Washington, DC, USA*.

Chen, J., C. Li, Z. Ristovski, A. Milic, Y. Gu, M. S. Islam, S. Wang, J. Hao, H. Zhang, C. He, et al. (2017). A review of biomass burning: Emissions and impacts on air quality, health and climate in China. *Science of the Total Environment 579*, 1000–1034.

Dipoppa, G. and S. Gulzar (2022). Fires: The political economy and health impacts of crop burning in South Asia. *Working Paper*.

Edwards, R. B., W. P. Falcon, G. Hadiwidjaja, M. M. Higgins, R. L. Naylor, and S. Sumarto (2020). Fight fire with finance: A randomized field experiment to curtail land-clearing fire in Indonesia. Working Paper 55-e - 2020, Tim Nasional Percepatan Penanggulangan Kemiskinan.

Engel, S., S. Pagiola, and S. Wunder (2008). Designing payments for environmental services in theory and practice: An overview of the issues. *Ecological economics 65*(4), 663–674.

Fuller, R., P. J. Landrigan, K. Balakrishnan, G. Bathan, S. Bose-O'Reilly, M. Brauer, J. Caravanos, T. Chiles, A. Cohen, L. Corra, et al. (2022). Pollution and health: a progress update. *The Lancet Planetary Health*.

Garg, T., M. Jagnani, and H. K. Pullabhotla (2021). Agricultural labor exits increase crop fires. Working Paper.

Ghude, S. D., D. Chate, C. Jena, G. Beig, R. Kumar, M. Barth, G. Pfister, S. Fadnavis, and P. Pithani (2016). Premature mortality in India due to PM2.5 and ozone exposure. *Geophysical Research Letters 43*(9), 4650–4658.

Govardhan, G., R. Ambulkar, S. Kulkarni, A. Vishnoi, P. Yadav, B. A. Choudhury, M. Khare, and S. D. Ghude (2023). Stubble-burning activities in north-western india in 2021: Contribution to air pollution in delhi. *Heliyon*.

Jack, B. K. (2013). Private information and the allocation of land use subsidies in Malawi. *American Economic Journal: Applied Economics 5*(3), 113–35.

Jack, K., S. Jayachandran, N. Kala, and R. Pande (2021). Paying farmers not to burn: A randomized trial of payments for ecosystem services in India. *AEA RCT Registry*.

Jain, N., A. Bhatia, H. Pathak, et al. (2014). Emission of air pollutants from crop residue burning in India. *Aerosol and Air Quality Research 14*(1), 422–430.

Jayachandran, S., J. De Laat, E. F. Lambin, C. Y. Stanton, R. Audy, and N. E. Thomas (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science 357*(6348), 267–273.

Kaczan, D., A. Pfaff, L. Rodriguez, and E. Shapiro-Garza (2017). Increasing the impact of collective incentives in payments for ecosystem services. *Journal of Environmental Economics and Management 86*, 48–67.

Kramer, B. and F. Ceballos (2018). Enhancing adaptive capacity through climate-smart insurance: Theory and evidence from India. Working paper, International Food Policy Research Institute.

Kumar, P., S. Rajpoot, V. Jain, S. Saxena, S. Ray, et al. (2019). Monitoring of rice crop in Punjab and Haryana with respect to residue burning. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 42*, 31–36.

Lan, R., S. D. Eastham, T. Liu, L. K. Norford, and S. R. Barrett (2022). Air quality impacts of crop residue burning in India and mitigation alternatives. *Nature Communications 13*(1), 6537.

Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies 76*(3), 1071–1102.

Lee, K. and M. Greenstone (2021). Air Quality Life Index annual update. Technical report, Energy Policy Institute at the University of Chicago.

Madheswaran, S. (2007). Measuring the value of statistical life: estimating compensating wage differentials among workers in India. *Social indicators research 84*, 83–96.

Majumder, A., S. Madheswaran, et al. (2018). *Value of statistical life in India: A hedonic wage approach*. Institute for Social and Economic Change.

National Green Tribunal (2015). Vikrant Kumar Tongad v. Environment Pollution Authority & Ors. Judgement.

Nian, Y. (2023). Incentives, penalties, and rural air pollution: Evidence from satellite data. *Journal of Development Economics*, 103049.

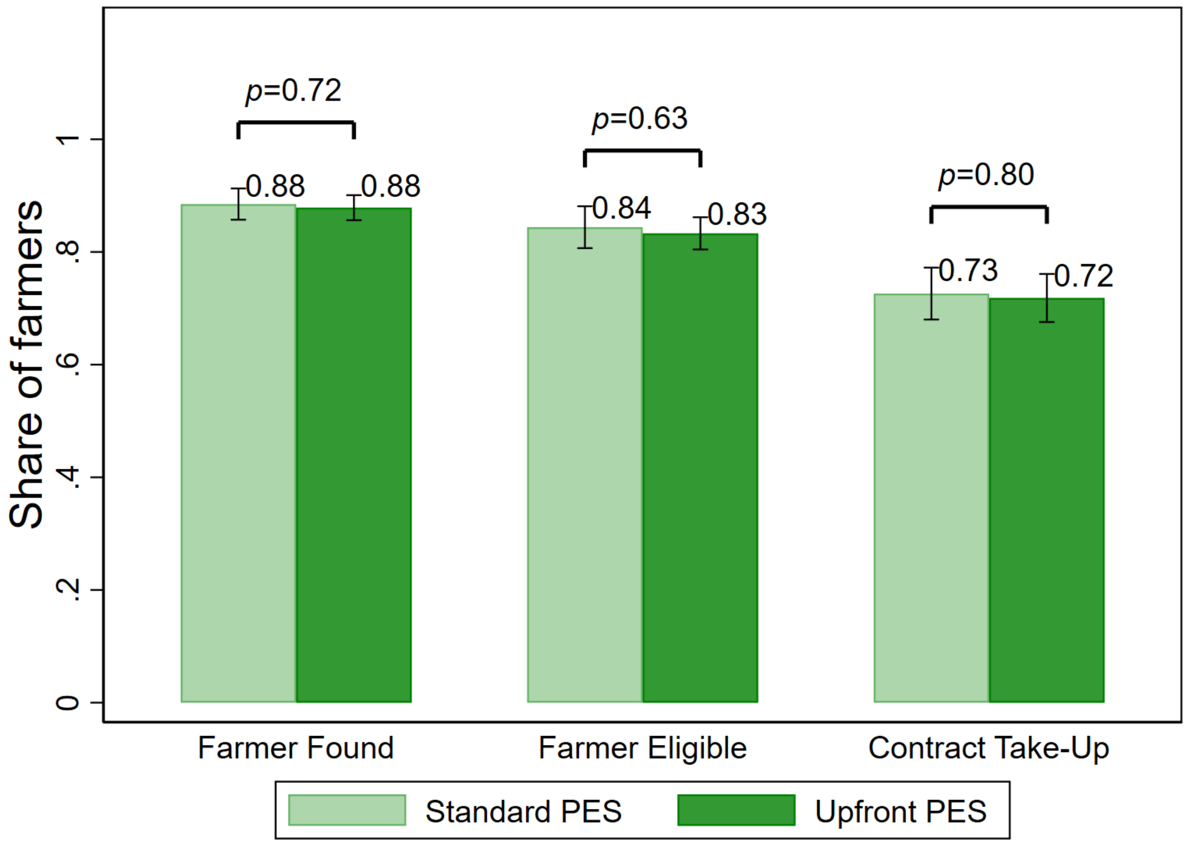
Oanh, N. T. K., D. A. Permadi, P. K. Hopke, K. R. Smith, N. P. Dong, and A. N. Dang (2018). Annual emissions of air toxics emitted from crop residue open burning in Southeast Asia over the period of 2010–2015. *Atmospheric Environment 187*, 163–173.

Oliva, P., B. K. Jack, S. Bell, E. Mettetal, and C. Severen (2020). Technology adoption under uncertainty: Take-up and subsequent investment in Zambia. *Review of Economics and Statistics 102*(3), 617–632.

Walker, K., B. Moscona-Remnitz, K. Jack, S. Jayachandran, N. Kala, R. Pande, J. Xue, and M. Burke (2022). Detecting crop burning in India using satellite data. Working Paper.

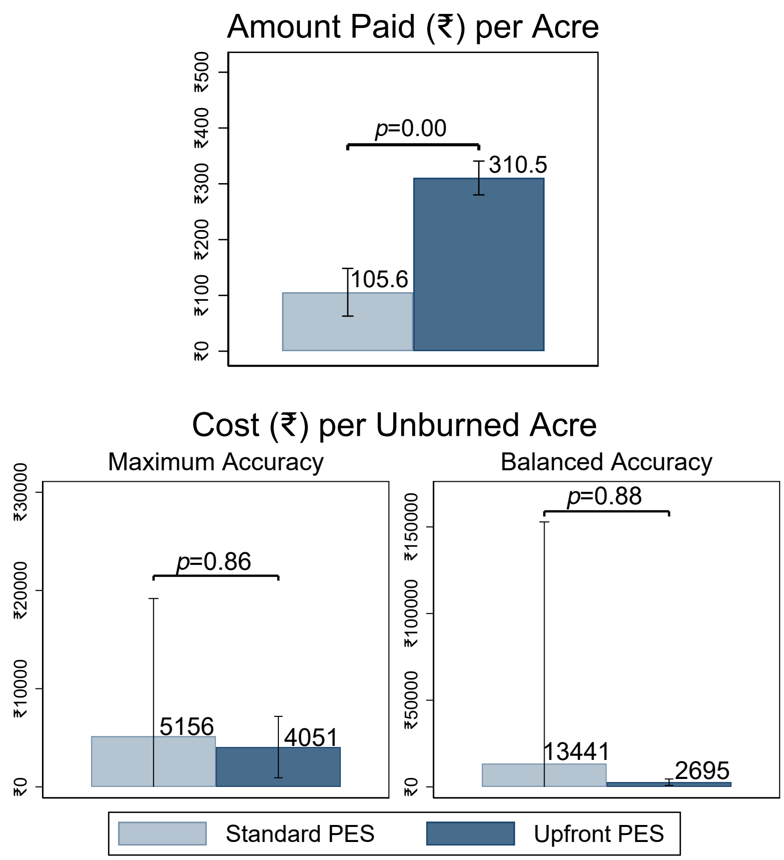
Wunder, S., S. Engel, and S. Pagiola (2008). Taking stock: A comparative analysis of payments for environmental services programs in developed and developing countries. *Ecological economics 65*(4), 834–852.

Figure 1: Contract Eligibility and Take-Up



Note: "Farmer Found" equals 1 if the respondent was available during the PES contract offer visit. "Farmer Eligible" equals 1 if the respondent was available, had a bank account, and had not yet managed his crop residue. "Contract Take-Up" equals 1 if the respondent signed a contract to participate in the PES program. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level.

Figure 2: Cost-Effectiveness



Note: "Amount Paid per Acre" is the per acre payment in ₹ that the farmer received. This includes the amount paid upfront for those in the Upfront PES treatment, plus the amount paid conditional on compliance for those in the Upfront and Standard PES treatment. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level. "Cost per Unburned Acre" is the "Amount Paid per Acre" divided by "Unburned" (Table 1), with standard errors calculated using the delta method.

Table 1: Contract Compliance, Not Burning, and CRM Use

	Complied with Contract	Unburned: Max Accuracy	Unburned: Balanced Accuracy	CRM techniques: Baler	CRM techniques: Seeder
	(1)	(2)	(3)	(4)	(5)
Standard PES	0.085	0.020	0.008	-0.010	-0.020
	(0.015)	(0.030)	(0.042)	(0.037)	(0.023)
Upfront PES	0.183	0.077	0.115	0.096	0.013
	(0.020)	(0.032)	(0.042)	(0.039)	(0.026)
p-val: Standard PES = Upfront PES	0.000	0.071	0.008	0.014	0.157
Control mean	0.000	0.091	0.202	0.199	0.102
Standard PES mean	0.084	0.098	0.198	0.171	0.087
Upfront PES mean	0.185	0.161	0.313	0.295	0.112
N	1668	1664	1664	1387	1387

Note: "Complied with Contract" equals 1 if the respondent called to request monitoring of his plots, and the monitoring determination was that the respondent complied with the contract, i.e., did not burn his crop residue. "Unburned" equals 1 if the farmer did not burn any of his plots based on the remote sensing model and a classification threshold that maximizes overall accuracy ("Max Accuracy") or balanced accuracy in predicting burned and unburned plots ("Balanced Accuracy"). "Baler" equals 1 if the farmer reported in the endline survey that he used a baler to manage his residue the previous fall. "Seeder" equals 1 if the farmer reported in the endline that he used a Happy Seeder or a Super Happy Seeder to manage his residue. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level.

Table 2: Liquidity and Distrust as Moderators of Treatment Effects

Panel A: Liquidity Constraints and Distrust

Outcome variable:	Complied with Contract		Unburned (Maximum Accuracy)	
Type of constraint:	Distrust (1)	Liquidity (2)	Distrust (3)	Liquidity (4)
Upfront PES	0.114	0.088	0.054	0.051
	(0.030)	(0.029)	(0.029)	(0.029)
Highly constrained	0.030	0.010	0.003	0.014
	(0.024)	(0.022)	(0.025)	(0.030)
Upfront PES × Highly constrained	-0.032	0.018	-0.025	-0.022
	(0.036)	(0.038)	(0.039)	(0.042)
Standard PES mean	0.083	0.084	0.104	0.105
Upfront PES mean	0.185	0.185	0.143	0.142
N	1172	1182	1168	1178

Panel B: Trust in Payment and Importance of Cash Shortage

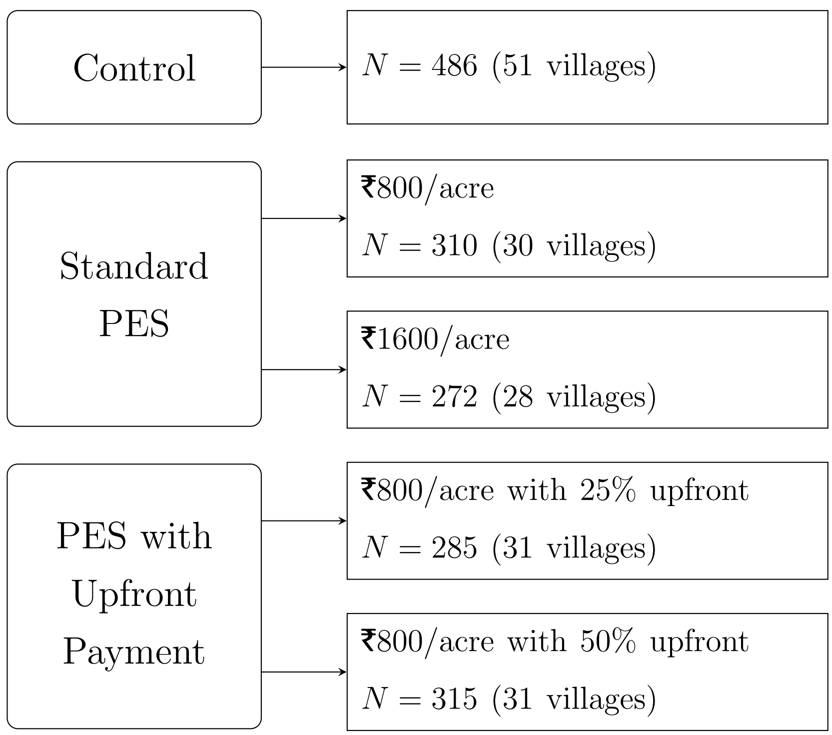
Outcome variable:	Trusted Payment (1)	Cash Shortage Not Important (2)
Upfront PES	0.068	0.038
	(0.028)	(0.043)
Standard PES mean	0.854	0.441
N	580	584

Note: Panel A: The row labeled "Type of constraint" indicates the heterogeneity variable analyzed in each column. "Liquidity" is an index of liquidity constraints, including constrained access to cash and loans. "Distrust" is an index of the farmer's distrust in categories of people and organizations. All heterogeneity variables are binary and equal 1 if the farmer's constraints are above the sample median. The outcome variable is indicated in the top row: "Complied with Contract" equals 1 if monitoring showed no signs of burning. "Unburned" equals 1 if the farmer did not burn any of his plots based on the remote sensing model and a classification threshold that maximizes overall accuracy ("Maximum Accuracy"). Treatment effects are estimated using a modified version of equation (1), which omits the control group and includes both a level and an interaction term (with Upfront PES) for the heterogeneity variable, includes strata fixed effects and clusters standard errors at the village level. The omitted group is the standard PES treatment. Panel B: "Trusted Payment" equals 1 if the respondent trusted that the payment by J-PAL would be made if they did not burn their paddy residue. "Cash Shortage Not Important" equals 1 if the respondent said that cash shortage was not an important factor when deciding which crop residue management method to use. These outcome variables are from the endline survey. Treatment effects are estimated using a modified version of equation (1), which omits the control group, includes strata fixed effects and clusters standard errors at the village level. The omitted category is the standard PES treatment. Only those who signed a contract are included in the sample.

Online appendices

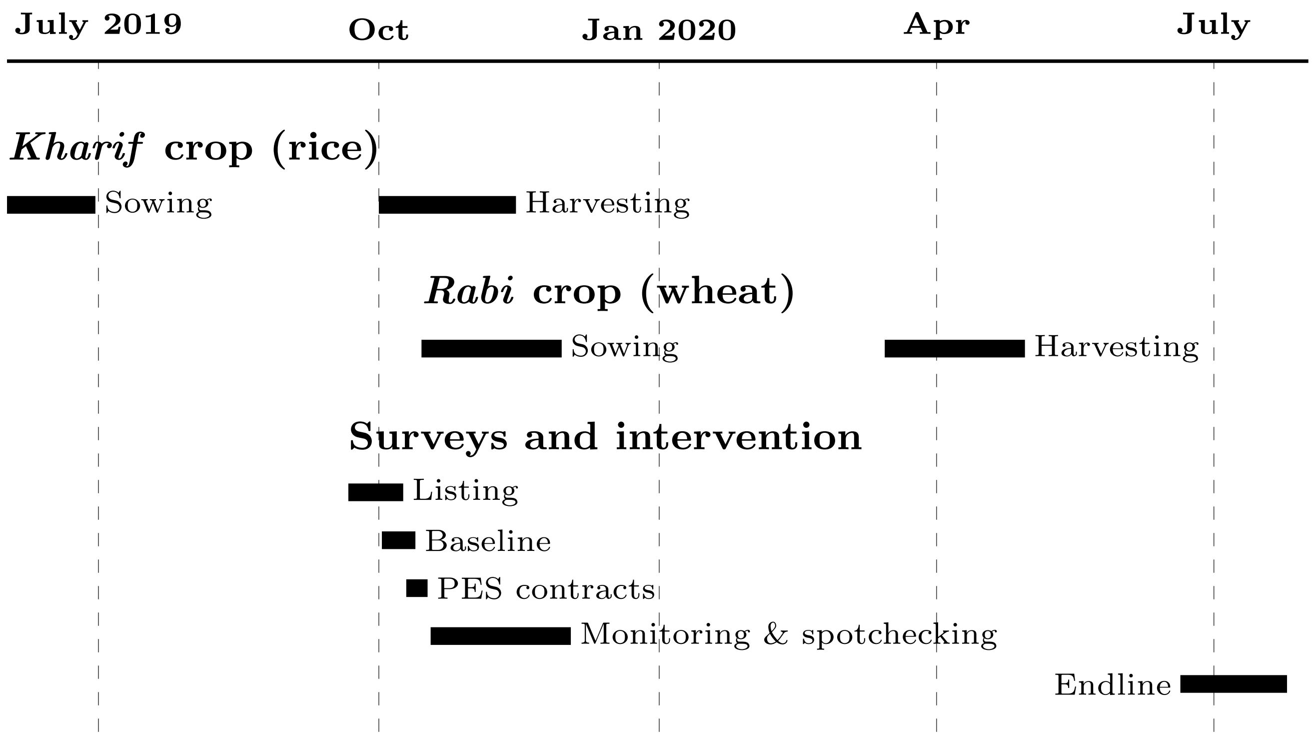
A.1 Tables and figures

Figure A.1: Experimental Design



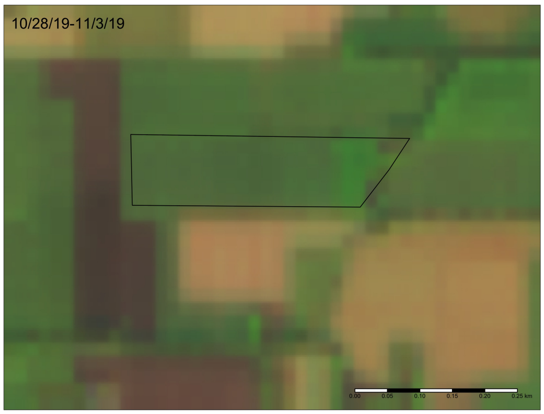
Note: Treatments are assigned at the village level. See text for additional detail.

Figure A.2: Timeline

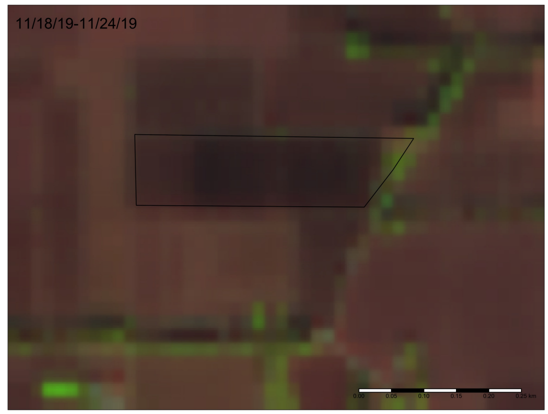


Note: Calendar of agricultural activities and timeline of data collection and implementation.

Figure A.3: Visual Signs of Burning in Imagery: Example



Around harvest time

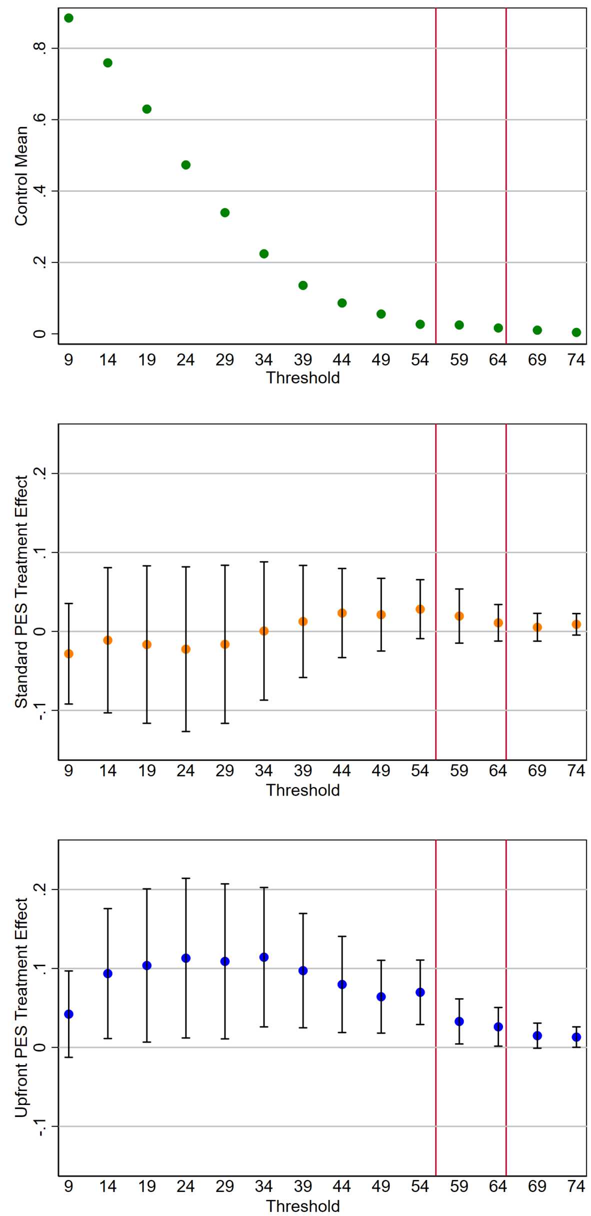


Just after burning

One week after burning

Note: Imagery from Sentinel-2 showing a study plot at different points in the agricultural season.

Figure A.4: Robustness of Treatment Effects on Not Burning



Note: The graphs show the control mean and treatment effects estimated using equation (1) on binary remote sensing measures of burning outcomes (unburned) based on different classification thresholds. The classification thresholds are indicated on the x-axis. The binary remote sensing measures take value 1 if the farmer did not burn any of his plots. The top panel shows the mean in the control group. The middle panel shows the treatment effects of the standard PES treatment arm. The bottom panel shows the treatment effect of the upfront PES treatment arm. The two red lines in the middle and bottom graph indicate the thresholds that maximize overall model accuracy (threshold at 65), and that classifies burning to balance type I and type II errors (threshold at 56).

Table A.1: Comparison of Study Sample, Cooperative Listing, and Census Sample

	Census (1)	Cooperative members (2)	Study eligible (3)	Study enrolled (4)	Diff Coop. - Census (5)	Diff Coop. - Study (6)
Age (years)	46.79	46.99	46.53	48.34	0.20	1.35
	(14.31)	(14.31)	(14.53)	(12.82)	[1.02]	[2.22]
Total experience in agriculture (years)	25.66	26.29	25.05	28.92	0.63	2.63
	(14.58)	(14.72)	(14.25)	(13.39)	[1.04]	[2.31]
Total area of paddy land in acres (reported)	7.71	7.99	5.54	5.26	0.28	-2.73
	(8.03)	(7.69)	(2.93)	(2.47)	[0.56]	[0.58]
1(Knowledge of CRM techniques)	0.87	0.89	0.86	0.79	0.02	-0.10
	(0.33)	(0.32)	(0.35)	(0.41)	[0.02]	[0.07]
1(Tried a CRM technique other than burning)	0.90	0.90	0.85	0.74	-0.00	-0.16
	(0.30)	(0.31)	(0.36)	(0.45)	[0.02]	[0.07]
Distrust index excluding distrust in family (continuous)	-0.01	-0.32	-0.03	0.80	-0.31	1.12
	(3.49)	(3.43)	(3.57)	(3.92)	[0.25]	[0.67]
1(Aware of government PES program)	0.37	0.36	0.38	0.31	-0.01	-0.06
	(0.48)	(0.48)	(0.49)	(0.47)	[0.03]	[0.10]
1(Applied to government PES program 2019)	0.19	0.18	0.16	0.19	-0.01	0.01
	(0.40)	(0.39)	(0.37)	(0.40)	[0.03]	[0.08]
N	479	339	190	38		

Note: Standard deviations reported in parentheses and standard errors reported in brackets. Column 1 includes the sample of respondents in the census survey; column 2 includes the subgroup of participants in the census survey who are part of the local farmers' cooperative society; column 3 restricts the census sample to those respondents who would have been eligible for the baseline survey; column 4 includes the sample of census respondents in the study. Columns 1 to 4 are the means in the samples, and columns 5 and 6 are the differences between the means.

Table A.2: Summary Statistics and Balance

	N	Control Mean	Control SD	Treatment vs Control	Standard vs Control	Upfront vs Control	Upfront vs Standard
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Demographics							
Age (years)	1668	48.675	12.732	-0.158	-0.448	0.124	0.610
				(0.751)	(0.816)	(0.825)	(0.653)
Total experience in agriculture (years)	1668	28.055	13.144	-0.184	-0.452	0.078	0.522
				(0.788)	(0.860)	(0.874)	(0.732)
Highest educational class passed	1658	7.213	4.197	-0.147	-0.200	-0.096	0.114
				(0.228)	(0.265)	(0.270)	(0.283)
1(Ever signed a written contract)	1440	0.483	0.500	-0.048	-0.049	-0.048	0.001
				(0.039)	(0.044)	(0.044)	(0.041)
Panel B: Income							
Total income	1602	125.694	172.588	-4.655	1.060	-10.190	-10.352
				(11.386)	(12.886)	(13.798)	(14.493)
Non-agricultural income	1455	18.076	66.407	-1.393	-2.545	-0.277	3.150
				(4.563)	(5.136)	(6.630)	(8.084)
Total agricultural profit	1521	114.177	155.748	-2.759	4.674	-9.905	-14.483
				(11.246)	(12.700)	(12.865)	(12.426)
Total area of land in acres (measured)	1668	4.986	2.816	0.327	0.350	0.304	-0.049
				(0.173)	(0.203)	(0.188)	(0.181)
Paddy production in 1000kg	1513	13.250	9.593	0.684	1.069	0.308	-0.768
				(0.625)	(0.736)	(0.700)	(0.722)
Panel C: Heterogeneity variables							
Liquidity constraints index	1668	0.488	0.500	0.016	0.027	0.005	-0.016
				(0.040)	(0.044)	(0.046)	(0.043)
Distrust index	1655	0.476	0.500	0.043	0.058	0.029	-0.032
				(0.035)	(0.039)	(0.040)	(0.034)
CRM information constraints index	1676	0.444	0.497	0.026	0.062	-0.009	-0.076
				(0.034)	(0.040)	(0.039)	(0.041)
CRM access constraints index	1651	0.445	0.497	0.076	0.078	0.073	-0.009
				(0.033)	(0.036)	(0.038)	(0.034)
CRM negative beliefs index	1676	0.500	0.501	0.069	0.095	0.043	-0.060
				(0.035)	(0.039)	(0.038)	(0.032)
Panel D: Burning							
1(Burned paddy residue in 2018)	1576	0.684	0.465	0.025	0.044	0.006	-0.037
				(0.034)	(0.037)	(0.039)	(0.035)
P-value of joint F-test				0.487	0.492	0.683	0.805

Note: Column 1 shows the number of non-missing observations in the baseline survey out of a total of 1,668 observations; 486 observations for the control group and 1,182 observations for the treatment groups. Columns 2 and 3 show the summary statistics for the control group in the baseline. Column 4 shows the coefficient from regressing the baseline variable on an indicator for any treatment. Columns 5 and 6 are the coefficients from regressing the baseline variable on separate indicators for the standard and upfront PES treatments. Column 7 shows the coefficient from regressing the baseline variable on an indicator for the upfront PES treatment, omitting the control group (coefficients are relative to standard PES). Income variables cover past 12 months and are measured in ₹1,000. Heterogeneity variables in Panel C are binary. Coefficients are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level.

Table A.3: Attrition from the Endline Survey

	Attrition
	(1)
Standard PES	0.051
	(0.025)
Upfront PES	0.044
	(0.025)
p-val: Standard PES = Upfront PES	0.786
Control mean	0.130
Standard PES mean	0.187
Upfront PES mean	0.182
N	1668

Note: "Attrition" equals 1 if the respondent was not in the endline. Coefficients are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level.

Table A.4: Heterogeneity of Attrition from the Endline Survey

Outcome variable:	Attrition																
Heterogeneity variable:	Age	Agric. Exp.	Educ.	Ever Signed Contract	Income	Non-Agric. Income	Agric. Revenue	Land Area	Paddy Prod.	Liquidity Const.	Distrust	Info. Const.	Access Const.	Neg. Beliefs	Burned Paddy Residue in 2018	Unburned (Balanced)	Unburned (Maximum)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Standard	-0.043	0.001	0.079	0.059	0.050	0.071	0.052	0.110	0.093	0.052	0.036	0.053	0.057	0.040	0.034	0.058	0.061
	(0.094)	(0.056)	(0.049)	(0.035)	(0.029)	(0.024)	(0.027)	(0.046)	(0.039)	(0.032)	(0.029)	(0.029)	(0.033)	(0.036)	(0.046)	(0.027)	(0.025)
Upfront	-0.029	0.035	0.043	0.045	0.049	0.050	0.041	0.074	0.041	0.045	0.071	0.046	0.045	0.042	0.030	0.035	0.040
	(0.096)	(0.054)	(0.045)	(0.033)	(0.030)	(0.027)	(0.027)	(0.049)	(0.041)	(0.034)	(0.031)	(0.027)	(0.033)	(0.036)	(0.040)	(0.028)	(0.026)
Het. Var.	-0.001	-0.001	0.001	0.016	0.002	0.006	0.000	0.007	0.001	0.033	0.031	0.040	0.013	-0.005	-0.014	-0.011	0.054
	(0.001)	(0.001)	(0.004)	(0.030)	(0.001)	(0.003)	(0.001)	(0.006)	(0.002)	(0.029)	(0.026)	(0.026)	(0.032)	(0.031)	(0.037)	(0.038)	(0.059)
Standard x Het. Var.	0.002	0.002	-0.004	0.003	-0.000	-0.008	-0.000	-0.012	-0.003	-0.002	0.028	-0.008	-0.013	0.020	0.040	-0.035	-0.102
	(0.002)	(0.002)	(0.006)	(0.048)	(0.001)	(0.003)	(0.001)	(0.008)	(0.002)	(0.045)	(0.041)	(0.040)	(0.046)	(0.050)	(0.056)	(0.052)	(0.075)
Upfront x Het. Var.	0.001	0.000	0.000	0.016	-0.002	-0.007	-0.000	-0.006	-0.000	-0.002	-0.053	-0.004	0.000	0.004	0.029	0.036	0.007
	(0.002)	(0.002)	(0.005)	(0.048)	(0.001)	(0.003)	(0.001)	(0.008)	(0.002)	(0.045)	(0.038)	(0.043)	(0.044)	(0.045)	(0.049)	(0.052)	(0.080)
p-val: Standard x Het. Var. = Upfront x Het. Var.	0.801	0.401	0.455	0.815	0.305	0.724	0.132	0.473	0.138	0.998	0.050	0.933	0.760	0.751	0.838	0.147	0.125
p-val: Standard x Het. Var. = 0	0.315	0.332	0.456	0.944	0.832	0.029	0.853	0.139	0.168	0.964	0.495	0.843	0.777	0.690	0.472	0.503	0.178
p-val: Upfront x Het. Var. = 0	0.433	0.845	0.975	0.742	0.265	0.026	0.836	0.470	0.969	0.966	0.166	0.925	0.996	0.928	0.553	0.493	0.933
Control mean	0.130	0.130	0.130	0.127	0.134	0.128	0.131	0.130	0.128	0.130	0.128	0.130	0.128	0.130	0.122	0.130	0.130
Standard PES mean	0.187	0.187	0.186	0.193	0.187	0.191	0.188	0.187	0.183	0.187	0.188	0.187	0.186	0.187	0.190	0.188	0.188
Upfront PES mean	0.182	0.182	0.182	0.184	0.171	0.173	0.179	0.182	0.174	0.182	0.181	0.182	0.183	0.182	0.178	0.183	0.183
N	1668	1668	1658	1440	1602	1455	1603	1668	1513	1668	1655	1668	1651	1668	1576	1664	1664

Note: "Attrition" equals 1 if the respondent was not in the endline. Het. Var. is the heterogeneity variable, shown in the column title. "Agric. Exp." refers to the total experience in agriculture (years). "Educ." refers to the highest educational class passed. "Ever Signed Contract" is a dummy taking value 1 if the farmer ever signed a written contract before and 0 otherwise. "Income" refers to the total income in ₹'s in the past 12 months. "Non-Agric. Income" refers to non-agricultural income in ₹in the past 12 months. "Agric. Revenue" refers to the total revenue from agriculture in 1000 ₹. "Land Area" refers to the total area of land in acres. "Paddy Prod." refers to the paddy production in 1000kg. "Financial Const." refers to a financial constraints index. "Distrust" refers to an index indicating the farmer's distrust in categories of people and organizations. "Info. Const." refers to a CRM information constraints index. "Access Const." refers to a CRM access constraints index. "Neg. Beliefs" refers to a CRM negative beliefs index. "Burned Paddy Residue in 2018" equals 1 if the farmer reported having burned paddy residue in 2018 and 0 otherwise. "Unburned (Balanced)" refers to the remote sensing measure of not-burning using the balanced accuracy threshold, and "Unburned (Maximum)" refers to the remote sensing measure of not-burning using the maximum accuracy threshold. The number of observations (N) reflects non-missing observations of the heterogeneity variable. Coefficients are estimated using a modified version of equation (1), which includes both a level and treatment interactions for the heterogeneity variable, includes strata fixed effects and clusters standard errors at the village level.

Table A.5: Treatment Effects on Measures of Not Burning

	Unburned (Max Accuracy) at plot-level (1)	Spot Check (2)
Standard PES	0.022	0.013
	(0.036)	(0.076)
Upfront PES	0.101	0.103
	(0.036)	(0.073)
p-val: Standard PES = Upfront PES	0.023	0.234
Control mean	0.150	0.373
Standard PES mean	0.154	0.364
Upfront PES mean	0.265	0.456
N	2875	714

Note: "Unburned (Max Accuracy) at Plot-Level" equals 1 if a plot was not burned according to a remote sensing measure that classifies burning to maximize overall model accuracy. "Spot Check" equals 1 if a plot showed no sign of burning during a random spot check. Plot level regressions are weighted by the inverse of the number of plots the farmer has. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level.

Table A.6: Treatment Effects Disaggregated by Subtreatment

	Contract Take-Up (1)	Complied with Contract (2)	Unburned (Max Accuracy) (3)
800/acre	0.743	0.068	0.007
	(0.030)	(0.016)	(0.033)
1600/acre	0.707	0.104	0.036
	(0.036)	(0.025)	(0.038)
800/acre with 25% Upfront	0.737	0.177	0.056
	(0.030)	(0.029)	(0.032)
800/acre with 50% Upfront	0.702	0.189	0.094
	(0.029)	(0.029)	(0.046)
p-val: 800/acre = 1600/acre	0.441	0.219	0.461
p-val: 800/acre = 800/acre with 25% Upfront	0.885	0.001	0.170
p-val: 800/acre = 800/acre with 50% Upfront	0.310	0.000	0.059
p-val: 1600/acre = 800/acre with 25% Upfront	0.510	0.051	0.617
Control mean	0.000	0.000	0.091
N	1668	1668	1664

Note: "Complied with Contract" equals 1 if the respondent called to request monitoring of his plots, and monitoring led to the conclusion that the respondent complied with the contract i.e. did not burn his paddy residue. "Unburned" equals 1 if the farmer did not burn any of his plots. "800/acre" is the Standard PES arm that received ₹800 per acre conditional on not burning. "1600/acre" is the Standard PES arm that received ₹1600 per acre conditional on not burning. "800/acre with 25% Upfront" is the upfront PES arm that received 25% of ₹800 per acre unconditionally upfront and 75% conditional on not burning. "800/acre with 50% Upfront" is the upfront PES arm that received 50% of ₹800 per acre unconditionally upfront and 50% conditional on not burning. Treatment effects are estimated using a modified version of equation (1), which includes indicators for each subtreatment, includes strata fixed effects and clusters standard errors at the village level.

Table A.7: Crop Residue Management Methods: Lee Bounds

	CRM techniques	
	Baler	Seeder
Standard PES		
Lower bound	-0.025	-0.028
	(0.027)	(0.021)
Upper bound	0.036	0.047
	(0.025)	(0.017)
Upfront PES		
Lower bound	0.088	0.006
	(0.030)	(0.022)
Upper bound	0.145	0.068
	(0.028)	(0.019)

Note: "Baler" equals 1 if the farmer reported in the endline that he used a baler in the 2019 Kharif season. "Seeder" equals 1 if the farmer reported in the endline that he used a Happy Seeder or a Super Happy Seeder in the 2019 Kharif season. Lee bounds correspond to the treatment effect estimates reported in Table 1. To construct bounds, we trim observations from the control group within strata and include strata fixed effects in the estimation because our randomization is stratified.

Table A.8: Effects on Agricultural Yield and Sowing Delays

	Paddy Yield (1)	Wheat Yield (2)	Days (3)
Standard PES	-0.026	-0.013	-0.217
	(0.039)	(0.015)	(0.643)
Upfront PES	-0.066	0.008	-0.120
	(0.045)	(0.015)	(0.627)
p-val: Standard PES = Upfront PES	0.356	0.151	0.881
Control mean	1.249	0.745	18.364
Standard PES mean	1.237	0.736	17.943
Upfront PES mean	1.194	0.756	18.380
N	1367	1378	1386
Lee Bounds			
Standard PES			
Lower bound	-0.103	-0.035	-1.032
	(0.037)	(0.013)	(0.552)
Upper bound	0.037	0.008	0.320
	(0.037)	(0.015)	(0.524)
Upfront payment PES			
Lower bound	-0.113	-0.013	-0.937
	(0.037)	(0.010)	(0.532)
Upper bound	0.005	0.027	0.425
	(0.037)	(0.012)	(0.505)

Note: "Paddy Yield" is the amount of paddy produced in Kharif 2019 (log of 1000 kg per acre). "Wheat Yield" is the amount of wheat produced in Rabi 2020 (log of 1000 kg per acre). "Days" is the number of days after the paddy harvest that passed before the farmer started sowing the Rabi crop. The bottom panel shows the Lee bounds for the treatment effects. To construct bounds, we trim observations from the control group within strata and include strata fixed effects in the estimation because our randomization is stratified.

Table A.9: Heterogeneity of Treatment Effects on Contract Take-Up

Outcome variable:	Program Take-Up	
Type of constraint:	Liquidity Constraints (1)	Distrust (2)
Upfront PES	0.004	-0.018
	(0.040)	(0.041)
Highly constrained	0.020	0.024
	(0.036)	(0.042)
Upfront PES × Highly constrained	-0.015	0.035
	(0.051)	(0.059)
Pooled PES mean	0.734	0.735
N	1182	1172

Note: The row labeled "Type of constraint" indicates the heterogeneity variable: "Liquidity Constraints" is an index indicating liquidity constraints, including constrained access to cash and loans. "Distrust Constraints" is an index indicating the farmer's distrust in categories of people and organizations. All indices are binary and take value 1 if the farmer's constraint is larger than or equal to the median. The outcome variable is indicated in the top row of the table: "Program Take-Up" equals 1 if the respondent signed a contract to participate in the PES program. Treatment effects are estimated using a modified version of equation (1), which omits the control group and includes both a level and an interaction term (with upfront PES) for the heterogeneity variable, includes strata fixed effects and clusters standard errors at the village level.

Table A.10: Heterogeneity of Pooled Treatment Effects on Contract Compliance by CRM Equipment Constraints

Outcome variable:	Complied with Contract		
Type of constraint:	Information Constraints	Access Constraints	Negative Beliefs about Burning Alternatives
	(1)	(2)	(3)
Highly constrained	-0.063	-0.004	-0.040
	(0.019)	(0.024)	(0.020)
Pooled PES mean	0.135	0.136	0.135
N	1182	1168	1182

Note: The row labeled "Type of constraint" indicates the heterogeneity variable: "Information Constraints" is an index indicating the farmer's lack of knowledge about CRM equipment. "Access Constraints" is an index indicating the farmer's difficulties in accessing CRM equipment. "Negative Beliefs about Burning Alternatives" is an index indicating the strength of the farmer's negative beliefs about the impact of CRM equipment on soil health and yield as compared to burning. All indices are binary and take value 1 if the farmer's constraints are larger than or equal to the median. The outcome variable is indicated in the top row: "Complied with Contract" equals 1 if the respondent called to request monitoring of his plots, and the monitoring determination was that the respondent complied with the contract, i.e., did not burn his crop residue. Treatment effects are estimated using a modified version of equation (1), which omits the control group and includes both a level and an interaction term (with upfront PES) for the heterogeneity variable, includes strata fixed effects and clusters standard errors at the village level.

A.2 Intervention script

Program description

Our organization is working on agricultural and environmental issues and we want to help farmers manage paddy stubble after the paddy harvest this season. I am here to share details of a program that we are introducing to some farmers in this village during the paddy crop season in the month of October and November 2019.

To encourage farmers to manage paddy stubble in an environmentally-friendly manner, we will offer you an agreement that will pay you if you do not burn your paddy field(s) this season. We will compensate you at a rate of [treatment rate] per acre (up to a max. of [treat rate x 100]). You may use any alternate methods of managing the residue. Other than burning the stubble, we do not place any condition on what this method should be.

This monetary compensation will only be given to you if a monitor, during the months of October and November, assesses that that your paddy field has not been burned. If you are interested in participating, I will explain the terms and conditions of the agreement to you that will help you decide whether you want to enroll in the programme or not. If you are uncertain about signing the agreement because you are unsure whether you would be fulfilling the conditions of the contract, let me remind you that there is no harm in participating in the programme. If you burn, you will not be penalized in any way by us. If you do not burn, you will be given the reward. By signing you are only giving yourself a chance to win money.

If you would like someone in the house to help you make a decision and listen to the details of the programme, please feel free to invite them now. Please remember that whoever signs the agreement must have a bank account to enable payments at a later date.

Information handout

This document provides details on some of the items in the agreement and is to help the enrollee farmer with complying with the terms and conditions of the agreement.

Monitoring visits

1. The enrollee farmer is expected to initiate monitoring for all plots, with a maximum of two requests to J-PAL. All plots must be covered through these two requests.

2. Each request will result in up to two visits by J-PAL monitors. The second visit will only be performed if J-PAL determines that it is necessary to assess burning.

3. In addition to the requested and scheduled visits, J-PAL can also make unannounced visits to the plots for checks.

When to call for monitoring: The enrollee farmer should call once all the pre-sowing work related to stubble has been completed on the plots covered under the request. This means all activities related to stubble like removing or processing of stubble must have been completed and no further managing of stubble is required before sowing. In general, requests should be made at least four days before sowing. The request can occur if any of the following applies:

1. After the straw and stubble have been completely removed from the plot but no later than 4 days before sowing.

2. After the straw has been rolled into bales/bundles but no later than four days before sowing.

3. After the straw/stubble has been mixed or blended into the soil but no later than four days before sowing.

4. If using the Happy seeder or mulcher: once sowing preparation is complete but no later than four days before sowing. In these cases, a second monitoring visit will be made post sowing.

Remember, up to two requests can be initiated. If some plots are ready, call to schedule the first monitoring, keeping in mind that any plots not covered under the first request have to be monitored as part of the second request. If all plots are ready for monitoring, they can be inspected in a single visit.

Phone numbers for calling: xxx, xxx, xxx

What counts as burning? The agreement requires that farmers do not burn any of their plots. This will be broken if any of the following (or any other form of burning) are detected by the monitor. The farmer will not be eligible for payment if any of the following is detected during monitoring.

- Burning of the upper layer of loose straw left behind by the harvester.
- Burning of the standing stubble.
- Burning of straw collected in one part of the plot.
- Burning as mentioned above on any of the plots.

Important

1. J-PAL SA is not related to any government in any manner. The failure of the enrollee farmer to meet any term or condition in the agreement will not attract any penalty or fine, and no legal action will be taken. This is clearly stated in the agreement. We are only trying to find if this a good way to help the farmers with resolving the residue issue. We cannot impose any fines or penalties since we are not related to government.
2. The only consequence of not fulfilling any of the term or condition in the agreement will be that farmer will become ineligible for payment of amount as mentioned in the agreement.
3. In case the farmer does not request monitoring as specified above, J-PAL will not be liable to pay any amount as mentioned in the agreement. Decision on payment to be made will only be taken once all the plots have been fully monitored.
4. If after the first monitoring visit and after analyzing the observations recorded, the J-PAL SA team ascertains that burning happened in even one of the plots, no further monitoring visit will be conducted. In this case, the farmer will be ineligible to receive the payment.
5. At the time of the monitoring visit, we may also request you for bank account details. The bank account transfer is the fastest and easiest way to transfer the amount. After

the monitoring has been completed for all the plots and it is assessed that burning has not happened on any plots, the payment will be made directly into the account.

6. The enrollee farmer should keep the agreement and information handout safe for use later. The ID and phone numbers given on them are to be used for calling.

A.3 Sample contract

Standard PES: ₹800 per acre with no upfront payments

${village_id}

${a_hhid}

${resp_id}

Contract for Incentive Program Offering Payment for No-Burning on Paddy Plots

This Agreement is executed on ____________________[Insert date]

by and between ${resp_name},

residing at

____[Insert Enrollee Address]

AND

Abdul Latif Jameel Poverty Action Lab South Asia at the Institute for Financial Management and Research, which is registered under Society Registration Act 1860 (hereinafter referred to as "J-PAL SA"), located at Buhari Towers, 2nd Floor, 4, Moors Road, Chennai 600006

Background

J-PAL SA proposes to partner with [${resp_name}] (hereinafter referred to as "Enrollee") with the following summary of responsibilities.

Based on the field measurement completed in a previous visit, (s)he cultivates _#ACRE____ acres of paddy currently.

Summary of responsibilities

J-PAL SA

1. Visit Enrollee's paddy plots, which were mapped during the survey visit to the Enrollee that was already conducted, to assess whether burning occurred. This monitoring visit will take place once Enrollee informs J-PAL SA by phone, as described below. J-PAL will visit the plots to assess whether they have been burned within **3** days of being called by the Enrollee. 'Monitoring will be available only beginning on 15 October 2019 or today (whichever date is later). Enrollees that call to be monitored before this date cannot be monitored by J-PAL South Asia and therefore are not eligible for payment.
2. The J-PAL SA team will determine if the field has been burned based on the observations made by the monitor during their visit. The process of inspection is summarized below:
   a) The J-PAL SA monitor will visit all the paddy plots as measured during a previous visit.
   b) The monitor will physically inspect each plot for visual cues and record the observations. Based on the recorded observations during the visit, the J-PAL SA team will determine whether the field was burned or not.
3. If the paddy plots do not appear to be burned, as assessed by the J-PAL SA team, then J-PAL SA will provide Enrollee with an amount such that the total payment amount for not burning is Rs **800** per acre of enrolled land. The maximum overall payment is Rs **8000**. The payment amount for the Enrollee is Rs ${pes_amount}.

Enrollee

1. Enrollee confirms, by signing this agreement, that the paddy plots mapped during the survey visit represent all of his/her paddy plots. All paddy plots cultivated in the 2019 Kharif season must be enrolled.
2. After harvesting paddy and managing and processing stubble, and at least 4 days before sowing wheat or any other rabi crop, Enrollee is required to call J-PAL SA at the numbers provided on the information handout between the hours of 9:00 am and 5:00 pm, on any date between 15 October and 30 November 2019 to indicate that the fields are ready to be monitored. We will not be able to monitor before the above mentioned date and farmers requesting for monitoring to be conducted before the 15th October will not be eligible.
3. The Enrollee may request up to two monitoring visits to cover all paddy plots, for example, for some plots that are ready for monitoring early and others that are ready late. Each plot will be monitored up to two times.
4. The Enrollee will also allow additional, unscheduled monitoring to occur at any point in time.

5. If it is assessed by the J-PAL SA team that the field is not burnt, the Enrollee will receive a payment amount as indicated above. For the enrollee to be eligible for payment, no burning should have taken place on any of the plots.
6. The assessment of whether a field is burnt or not is not dependent on whether the field was burnt deliberately or accidentally, or by the Enrollee or someone else.

Payment and contract

1. J-PAL SA shall not be obligated to pay the Enrollee any amount in excess of what is mentioned above.
2. By signing this agreement, the Enrollee acknowledges that J-PAL SA reserves the right to rescind the payment of the aforementioned amount if the Enrollee fails to fulfil any of the responsibilities designated to him/her under “Summary of Responsibilities” and/or breach of the terms of this agreement in any manner or extent.
3. There will be no legal implications for the Enrollee for the breach of the agreement. J-PAL SA will not take any legal action against the Enrollee if one or more responsibilities remain unfulfilled under the agreement.

ACCEPTED BY:	ACCEPTED BY:
J-PAL SA	Enrollee
Signature	Signature
Name	Name
Location	Location
Date	Date

A.4 Survey questions used in constructing indices for heterogeneous treatment effects

This section details the (pre-specified) survey questions used in constructing the indices for heterogeneous treatment effects.

Financial constraints

1. If you needed to spend ₹5000 for agricultural equipment, would you have savings to draw on?
2. If you needed to spend ₹10,000 for agricultural equipment, would you have savings to draw on?
3. If you needed to spend ₹5000 for agricultural equipment, how easy would it be for you to get a loan for that amount?
4. If you needed to spend ₹10,000 for agricultural equipment, how easy would it be for you to get a loan for that amount?

These (standardized) variables are used to create an index, which is used to create a binary variable split at the median to denote high financial constraints.

Distrust

1. Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?
2. I'd like to ask you how much you trust people from various groups. Could you tell me for each whether you trust people from this group completely, somewhat, not very much or not at all?
    - People in your neighborhood?
    - Strangers?

3. Even if you have had very little or no contact with these following institutions, please base your answer on your general impression of these institutions.

    - The Punjab Government?
    - The village Panchayat?
    - The cooperative society?
    - Non-governmental organizations (NGOs)?
    - Financial Institutions like Banks/Insurance Companies?

CRM access barriers indices

We construct three indices to measure different aspects of CRM equipment access barriers. The first measures information constraints, the second access barriers, and the third beliefs about how CRM equipment impacts agriculture relative to burning. All questions except the first are asked about the CRM equipment farmers reported being familiar with.

Information Constraints

1. Do you know about any crop residue management techniques to manage paddy stubble?
2. Where can you rent it (CRM equipment) from?

Access Barriers

1. Do you own [CRM equipment] as an individual or member of a CHC or Coop?
2. Is using [CRM equipment] more expensive or less expensive than burning paddy stubble?
3. In days, how long would it take you to access crop residue management equipment for managing paddy stubble at harvest time this year?
4. Including all costs, how much would the equipment cost per acre (in Rs.)?
5. How many days would it take to manage paddy stubble using this equipment?

Negative Beliefs About CRM Equipment

- Is using [CRM equipment] better for long-term soil health or worse for soil health than burning paddy stubble?
- Does using [CRM equipment] help yield of rabi season or hurt yield of rabi season compared to burning paddy stubble?

A.5 Remote sensing model

This section provides additional detail on the construction of our remote sensing based outcome. For a complete description, please see Walker et al. (2022).

Model background The goal of the model is to detect whether a plot in our sample was burned at any point during the burn season (from October 10 to December 15, 2019) based on satellite imagery. While burn scars are obvious if the plot is observed by satellite soon after burning, this signal erodes quickly with time. With a temporal resolution of about two days, PlanetScope imagery can often capture burned plots within this critical window. However, clouds and other abnormalities result in a maximum gap between any two images of 8 days on average across plots in our sample. While Sentinel-2 imagery has a coarser temporal resolution of about eight days, it provides mid- and short-wave infrared (SWIR) bands that are able to detect signals of burning for a longer window post-burn. By combining observations from both sensors, we built a Random Forest (RF) model with an overall accuracy of 82% in detecting burning in smallholder rice plots.

Other studies have relied on burn detection based on active fires, using, for example, data from the Visible Infrared Imaging Radiometer Suite (VIIRS). The sensor has a spatial resolution of 375m, resulting in pixels that are around 140,000 m^2. A typical plot in our sample is around 10,000 m^2, and only a small share of farmers in a village are enrolled in the study, so existing active fire products are poorly suited to our measurement goals.

An overview of image processing for both types of satellite is as follows:

Imagery and image processing overview:

- PlanetScope: Four-band harmonized surface reflectance product from PlanetLabs
  - Resolution: Spatial: 3m, Temporal: 2.2-day on average (30-40 images per pixel)
  - Spectral bands: blue, green, red, Near Infrared (NIR)
  - Clouds: only included images with <10% cloud cover. Remaining clouds were masked using the unusable data masks (UDM2) provided with the imagery.

    - Pre-processing: atmospheric correction based on the 6SV2.1 radiative transfer code already applied to product. Harmonized product also incorporates data from Sentinel-2 to normalize the spectral response functions between sensors.

- Sentinel-2: Level-1C products from USGS, converted to surface reflectance
    - Resolution: Spatial: 10m for visible and NIR bands, 20m for shortwave infrared (SWIR) bands. Temporal: 7-8 days on average
    - Spectral bands: Blue, Green, Red, NIR, SWIR1, SWIR2
    - Clouds: Cloudless layers from Google Earth Engine with cloud probabilities $\leq .5$ cloud were used as initial masks, then inspected and expanded manually to remove remaining cloud shadows.
    - Pre-processing: Geometric and radiometric corrections applied as Level-1C product, converted to bottom-of-the atmosphere reflectance with SNAP toolkit.

Feature creation and selection: As model inputs, we used individual bands and derived indices aimed at reducing noise and amplifying the portion of the spectrum most associated with burning. These indices were taken from the literature on burn mapping with a focus on char detection rather than vegetation change, as our primary separation task is between bare soil (harvested and often tilled plots) and charred soil (burnt plots). For PlanetScope images, we used the Bare Soil Index (BSoI), which uses all four bands, the Char Index (CI), which uses all visible bands, and the Burn Area Index (BAI), Simple Ratio (SR) and NDVI, which use the red and NIR bands. For Sentinel-2 images, we also included several bands using one or both SWIR bands including the Burn Scar Index (BSI), Mid-Infrared Bispectral Index (MIRIBI), and two variations of the Normalized Burn Index (NBR and NBR2). See Walker et al. (2022) for background and equations.

We stacked all images that overlap with any of the study participants' rice plots into a time-series and created pixel-level features based on statistics from each band and index across time. Statistics included min, max, median, and outer percentiles. An additional temporal differencing measure (Vdiff) was calculated for each band and index with the goal of capturing the moment the pixel changed from unburned to burned. This Vdiff measure was calculated based on the largest drop (or spike) in the sequence of values (V) for V_{t+1} - V_t. We used SequentialFeatureSelector in the sklearn toolkit in Python to reduce the feature space to an optimal number of features (around 30) prior to the final analysis. Retained features are presented in Walker et al. (2022).

Recognizing that pixels along the edge of a plot likely present differently due to the mixture of plot/non-plot classes and different burn patterns at edges, we flagged border pixels. These pixels were observed to have low importance in the construction of the RF model and were thus dropped from our analysis.

Model training and assessment: Training data consists of 441 burned and 240 unburned labels collected on the ground from participant farmers in 2019. Unburned labels come from plots where participants invited a monitor to visit to confirm that the stubble was managed without burning. Burned labels come from observations during unannounced spot checks of participant plots.

We used pixel-level features from the 681 labeled plots to train a RF model to provide burn predictions. Although data was retained at the pixel level, full plots were held out from the training data for use in optimization and accuracy assessment. Plot-level holdouts were necessary because pixels within the same plot have highly correlated features; if some pixels within a plot were used for training while others were used for testing, overfitting of the model and overestimation of accuracy would occur. A single plot was held out each time while a RF model was generated with the remaining 680 plots. This process was repeated 680 times in a Leave-One-Out Cross-Validation (LOOCV) format. Model accuracy was assessed based on the prediction score for each plot in the run where it was left out of model training.

To convert from pixel to plot-level predictions, we aggregated on the plot-level mean of the continuous RF output (we also tried the median and various percentiles and found the mean to perform best). We then used two approaches to set the classification thresholds based on this mean score, with plots exceeding the threshold classified as burned. First, we maximized overall accuracy ("maximum accuracy") by iterating over each threshold percentile and selecting the threshold with the highest accuracy for the full labeled set of plots. Alternatively, to balance accuracy across burned and not-burned labels ("balanced accuracy"), we iterated the burn accuracy and the no-burn accuracy over each threshold percentile, interpolated these accuracies into smooth functions, and selected the percentile threshold with the greatest accuracy for the mean at the point of intersection (where burned accuracy equals unburned accuracy). We tested using Cohen's Kappa for threshold optimization, which measures how a classifier compares when evaluated against a random classifier. In this case, maximizing kappa resulted in the same threshold selection as the maximum accuracy approach for all versions of our model.

Following plot-level aggregation, our best RF model achieves 82 percent overall accuracy, with 91 percent accuracy in detecting burned plots but only 63 percent accuracy in detecting unburned plots (details in Walker et al. (2022)). When the burned/unburned errors are balanced with our balanced accuracy procedure, the overall accuracy is reduced to 78 percent. See Table A.11.

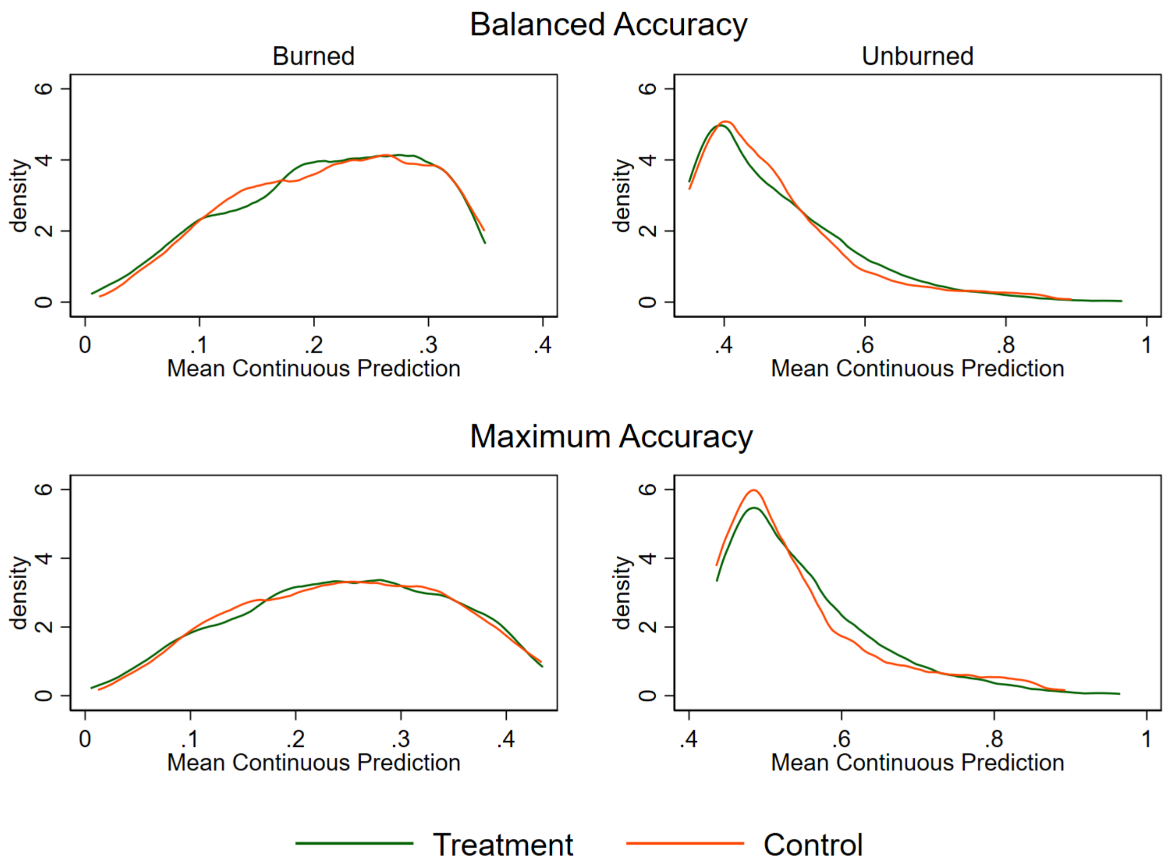
The RF model is trained using negative labels that are only available for the treatment group (and positive labels for both treatment and control groups). This could introduce bias into the classification if the spectral signature of not-burning is affected by treatment; if not-burning looks the same in treatment and control, this is not an issue. As one check on potential bias, Figure A.5 shows the distributions of the continuous random forest model output using plots not in the training set. Both for plots classified as burned and those classified as not-burned, the distributions are similar in the treatment and control groups. Formal statistical tests for equal distributions, conditional on classified burning status, confirm that there is no statistical difference.

Table A.11: Remote Sensing Model Accuracy in Holdout Sample

Accuracy model:	Unburned	
	Maximum Accuracy (1)	Balanced Accuracy (2)
Mean accuracy	0.82	0.78
False burn	0.13	0.08
False no burn	0.05	0.14
True burn	0.59	0.51
True no burn	0.22	0.27
No burn accuracy	0.63	0.76
Burn accuracy	0.92	0.79

Note: Accuracy statistics for remote sensing measures of burning, using different classifications thresholds. The true/false burn/no-burn rows show counts of the number of plots in each category. $N = 681$.

Figure A.5: Distribution of Random Forest Predictions by Treatment



Note: The left panel shows the distribution of the continuous remote sensing measure of not-burning for the plots classified as having been burned. The right panel shows the distribution of the same measure for plots classified as not having been burned. The continuous remote sensing measure ranges from 0 to 1, where higher values mean that it is more likely that the plot has not been burned.

A.6 Cost-benefit calculations

	Value	Details	Source
Deaths per year	36,980	86,000 total in 2018, 43% from Punjab. 2018 numbers, see table in supplement 5.	Lan et al. (2022)
Value per life, lower	688,000	640k in 2016 dollars (using 2016 exchange rate), converted to 2018 dollars using India's inflation rate	Majumder and Madheswaran. (2018)
Value per life, upper	5,800,000	800K in 1990 dollars, converted to 2018 (1990 exchange rate, India-specific inflation)	Madheswaran (2007)
Acres of non-basmati paddy in Punjab	6,011,980	2018 kharif non-basmati area, converted from ha	APEDA (2018)
Percent burned	0.66	2018-19 number	Kumar et al. (2019)
Acres burned	3,967,907		
Total mortality damages, Punjab burning	25,442,240,000		
Value per acre burned, lower in USD	6,412.01		
Value per acre burned, lower in Rupee	512,960.44		
USD upfront cost per acre (max)	50.63		
USD upfront cost per acre (balanced)	33.69		
Ratio of benefits to costs (max)	126.66		
Ratio of benefits to costs (balanced)	190.34		
Lives saved per acre	0.0093		
Cost per life saved, max	5,432.00		
Cost per life saved, balanced	3,614.63		

*Note that we are using 80 rupee per dollar, all 2018 values.

References

APEDA. (2018). Basmati Survey –Final Report-6 (Season 2018). Geotrans Technologies Pvt. Ltd. https://apeda.gov.in/apedawebsite/Announcements/Basmati_Crop_survey_Report_6_Season_2018.pdf

Kumar, P., Rajpoot, S. K., Jain, V., Saxena, S., & Ray, S. S. (2019). Monitoring of rice crop in Punjab and Haryana with respect to residue burning. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 31-36.

Lan, R., Eastham, S.D., Liu, T. *et al.* Air quality impacts of crop residue burning in India and mitigation alternatives. *Nat Commun* **13**, 6537 (2022). https://doi.org/10.1038/s41467-022-34093-z

Madheswaran, S. (2007). Measuring the value of statistical life: estimating compensating wage differentials among workers in India. *Social indicators research*, *84*, 83-96.

Majumder, A., & Madheswaran, S. (2018). *Value of statistical life in India: A hedonic wage approach*. Institute for Social and Economic Change.