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

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Abstract

We test the effectiveness of payments for ecosystem services (PES) in reducing crop residue burning, which contributes significantly to India's poor air quality. Standard PES contracts pay a monetary reward after verification that the participant has met a pro-environment condition (clearing agricultural 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. Despite providing a lower reward for compliance, contracts with partial upfront payment increase compliance by 10 percentage points, which is corroborated with satellite-based burning measurements. The cost per life saved using this strategy is \$4400. In contrast, standard PES has no effect on burning; the payments made are entirely inframarginal.

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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 among the region's half-billion residents by 6 to 9 years, resulting in one of the world's largest pollution-related health burdens (Ghude et al., 2016; Lee and Greenstone, 2021). The use of fires to clear agricultural land is a major source of this pollution.[1] Every winter, when farmers in North India burn rice stalk (residue) to clear fields, smoke blankets the region and drifts downwind to New Delhi, impacting the health of millions of people (Cusworth et al., 2018). A recent study estimates that crop residue burning caused 86,000 premature deaths in India in 2018 (Lan et al., 2022).

The Indian government subsidizes farm equipment that removes and manages residue without burning. Furthermore, in North India, burning residue has been declared illegal since 2015. Nonetheless, burning remains a common method of clearing residue (Aryal et al., 2023). Even with machinery subsidies, farmers' private costs to avoid burning are considerable. Furthermore, a powerful farmer lobby and the fact that residue burning imposes an inter-jurisdictional externality undermine state and local actors' incentives to enforce penalties and bans (Dipoppa and Gulzar, 2022).

Can payments for ecosystem services (PES) contracts, which compensate farmers for not burning crop residue, better incentivize farmers to stop doing so? PES programs, which condition cash transfers on avoiding environmentally harmful behavior, raise the private cost of environmental degradation and have been widely used to manage environmental externalities associated with land use (Jayachandran et al., 2017; Jack, 2013; Oliva et al., 2020).[2] However, the contextual and institutional features of lower-income countries may limit the efficacy of PES — and conditional cash transfers more broadly. Before receiving payment, PES participants must undertake a costly action to comply with the contract. Farmers may refuse to comply if they do not trust that the conditional payment will be made or if they lack cash on hand, before receiving the PES payment, to rent the farm

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

[2] In contrast, Edwards et al. (2020) find no impact of a bundled intervention of community-level training and payments to village governments for forest fire prevention.

equipment needed to avoid burning. PES contracts that offer partial advance payment may alleviate some of these constraints. An upfront payment sends a costly signal, increasing trust that the conditional payment will be made. It also provides liquidity at a time when farmers must invest in alternatives to burning.

We conducted a randomized controlled trial in 171 villages in Punjab during the 2019 rice growing season to assess the efficacy of standard PES versus PES with a partial upfront payment. We randomize villages into three groups: those in which farmers were not offered a contract (control), those in which a contract with payment conditional on verification that the farmer did not burn (standard PES) was offered, and those in which a contract that transferred part of the payment upfront and unconditional on compliance, with the remainder conditionally paid after verification (upfront PES) was offered.[3]

Our main finding is that, despite smaller conditional payments, upfront PES doubled the compliance rate and resulted in 10 percentage points higher contract compliance than standard PES. Remote sensing estimates of burning confirm this result, showing an 8 percentage point lower rate of burning for farmers offered upfront PES compared to the control group. Standard PES had no effect on burning compared to the control group; farmers who complied with the contract would not have burned even if PES had not been provided. Consistent with the compliance and burning results, endline survey data show that farmers in the upfront treatment arm were 9.5 percentage points more likely than those in the control group to report using baler equipment to bundle crop residue, while farmers in the standard PES treatment 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 issue.

While upfront contracts are more effective, farmers receive the upfront payments regardless of compliance, which may make them less *cost* effective than standard contracts. We calculate the cost per additional acre that is not burned. Upfront PES costs ₹4,050 ($51) per averted acre of burning, which is less than the (noisily) estimated analogous cost for

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

standard PES. Thus, upfront PES appears to be at least as cost-effective as standard PES, in addition to being more effective at reducing burning.

Prior research highlights the importance of contract design in agriculture (Carter et al., 2017), including the timing of insurance or loan payments (Burke et al., 2019; Fink et al., 2020; Casaburi and Willis, 2018), and how different contract features are bundled (Giné and Yang, 2009; Kramer and Ceballos, 2018). Conditional cash transfers are widely used to reward specific outcomes, and recent research tests the importance of payment conditionality (Baird et al., 2011; Akresh et al., 2013; Attanasio et al., 2015; Aker and Jack, 2023). Our contribution is to highlight the importance of contract design in environmental programs and show that small upfront payments can promote compliance.

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 grown in Kharif (June-October), and wheat in Rabi (November-April), with a short time window between crops. The introduction of mechanized harvesting in the 1980s facilitated the widespread adoption of this crop system, but 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.[4] Using satellite imagery from 2000 to 2018, Appendix Figure A.1 shows the rising incidence of fires across Punjab, as well as in our two study districts of Bathinda and Faridkot (DAAC, 2018).

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). Penalty-based policies have had limited impact due

[4]The time window for managing rice residue is made shorter by groundwater conservation laws that delay planting dates until around monsoon arrival, which Balwinder-Singh et al. (2019) show also contributes to increased residue burning.

to agricultural lobby opposition and weak enforcement. 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, which sows directly through paddy residue.The subsidy program did not cover *ex-situ* equipment that removes residue from the fields, such as balers, which bundle residue.[5]

Even with this subsidy scheme, CRM equipment rental costs remain high. Farmers typically rent equipment via hiring centers or agricultural cooperatives, which qualify for an 80% discount on equipment purchases. According to our baseline survey, the median rental cost for a Happy Seeder was ₹1,250 per acre, and the total cost of *in-situ* residue management was 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 seen as less damaging to yields.

Distrust and liquidity constraints are also plausible barriers to take-up of subsidies (which typically pay out with some delay). At baseline, only 13% of farmers said they entirely trusted the government, with only 7% trusting NGOs. Less than half had ₹5,000 in savings, and the majority stated that getting a ₹5,000 loan would be somewhat difficult or difficult. (A typical farmer in our sample has 5 acres of paddy production, so renting *in-situ* equipment would cost about ₹15,000, and renting a baler about ₹5,000.)

2.2 PES contracts and randomization design

We offered treated farmers standard PES contracts (58 villages) or partial upfront payment PES contracts (62 villages). Each of these treatments had two subtreatments, though we pre-specified that we would pool them 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 no-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 not burned.

[5]Baled straw is often used as an industrial heat source, displacing fossil fuel combustion. Nian (2023) provides evidence from China that the emergence of biomass power plants reduced agricultural residue burning.

Our second treatment arm addressed trust and liquidity concerns by making a portion of the payment 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 held fixed at ₹800. The difference between the two subtreatments was whether 25% or 50% was paid upfront. Appendix Figure A.2 summarizes the experimental design, which also includes a status quo control group (51 villages).[6] The timeline for data collection and agricultural activities is depicted in Appendix Figure A.3.

While upfront payments could theoretically be recouped from a non-compliant participant, doing so in practice is challenging (e.g., because participants are poor). Our contract explicitly made the upfront payment unconditional. This contract tweak could reduce compliance because the upfront component reduces the conditional amount, which is the farmer's incentive to comply. Furthermore, because some farmers who receive unconditional payments will fail to comply, the upfront payment may reduce PES cost-effectiveness even if compliance increases. Farmers' participation in all treatments was voluntary, and non-compliance with the PES contract was only 'penalized' by non-payment.

2.3 Sampling and baseline survey

Bathinda and Faridkot in Punjab were chosen as study districts because they have high rates of burning and few other organizations working there to encourage CRM adoption. We identified the 300 villages with the most cooperative members using farmer cooperative lists, and then screened farmers for eligibility by phone in Fall 2019. Farmers were eligible if they grew 2 to 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.

We conducted a baseline survey in October 2019 using the listing data, prioritizing villages

[6]Randomization occurred concurrently with the household listing and baseline surveys. We stratify on district, below/above median number of eligible households, baseline and listing survey completion, and a fifth strata of 15 villages that were added after the initial randomization to expand the sample size.

based on the number of eligible households. Baseline data collection ended once the target sample of 176 villages was reached. Enumerators moved down a randomly ordered list of households within a village, surveying the identified person on the cooperative member list, until either 16 surveys were completed or the list was exhausted. Villages with fewer than six completed baseline surveys were excluded for 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 CRM hurdles. Over half of household income for farmers in our study comes from agriculture, with a control group mean agricultural profit of ₹114,000 (median: ₹58,000). Less than half of the sample, 48%, had previously signed a written contract. As described in our pre-analysis plan, we use baseline data to construct distrust and financial constraints indices. We also construct CRM equipment access indices, which might affect PES program take-up or compliance but should do so equally 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 each plot for geocoded perimeter measurements. Plot borders formed the basis for monitoring farmers' contract compliance and for linking satellite imagery to plots.[7]

In early 2020, we censused four study villages to assess sample representativeness. 70% of farmers met the study inclusion criterion of being a cooperative member. Because we exclusively enrolled farmers who cultivated 12 acres or less (a criterion met by 80% of census farmers), study farmers cultivated 5.3 acres versus 7.7 acres for census farmers. Cooperative members are otherwise similar to census farmers (see Appendix Table A.1).

2.4 Contract implementation

J-PAL enumerators offered eligible farmers in treatment villages a PES contract, typically within a week of the baseline survey. Interested farmers were shown the contract corre-

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

sponding to their treatment arm, with the terms read aloud by the enumerator (Appendix A.3 shows a sample contract). Enumerators recorded whether the farmer was offered the PES contract, reasons for attrition (e.g., the household could not be found or did not have a bank account), and whether the farmer accepted the contract.[8] Farmers who took up the contract received a printed handout detailing contract terms and procedures for verification of burning outcomes. Their entire paddy acreage (as physically measured during the baseline survey) was enrolled. However, the contract capped the maximum amount a farmer could be paid at ₹16,000 in the ₹1,600 per acre arm and ₹8,000 in other treatment arms.[9] Direct bank deposits were made to farmers in the upfront PES arm 2-3 days after take-up.

Contract monitoring and enforcement required verifying that no paddy plots were burned. To detect whether burning had occurred, project staff had to visit the plot during the short time after the farmer had removed the residue, whether by CRM or burning, and before he had tilled the plot to sow the Rabi crop. A monitoring visit prior to the completion of residue management could not rule out future burning. After tilling, the signs of burning become much less visible. Because monitoring was necessary within this farmer-specific window of a few days, the farmer was made responsible for contacting J-PAL following residue management and at least four days before Rabi planting.[10] Up to two monitoring visits could be requested if, for example, separate plots had different planting schedules. Placing the onus for monitoring on the farmer may lower compliance, but was necessary for accurate, affordable compliance verification.

Visual inspection post-harvest and prior to tilling can fairly easily ascertain whether or not a plot was burned. The monitoring protocol required enumerators to observe and record multiple observations on each plot, such as burned straw or residue, grey or black ash on the soil, burned root residue, burned grass or weeds on the plot boundaries, and burned leaves or tree branches on the plot boundaries. They were told to inspect the plot perimeter and walk onto each plot and inspect the soil. Outcomes across plots were aggregated into a single

[8] Contract payments were made electronically, with bank account information only collected from treatment farmers. Only 6 farmers were screened out because they did not have a bank account.

[9] For the 7% of farmers who cultivated >10 acres of paddy (the study's eligibility criterion was ≤12 acres), the (potential) payment is constrained by the cap.

[10] Farmers who had not yet requested monitoring were contacted in the third week of October with a reminder to request monitoring when ready.

farmer-level compliance metric — any burning was a contract violation. Farmers who had complied were paid within 2-3 days of monitoring.

2.5 Outcome data

Contract take-up and compliance Contract take-up was recorded at the time of the contract offer. Our compliance outcome is an indicator for whether a farmer requested monitoring and was found not to have burned any of his plots during the monitoring visits.

Remote sensing measures Contract compliance is uninformative about the rate of burning among unmonitored farmers. Some control group farmers may have not burned, and some treatment group farmers who either did not enroll or did not call for monitoring may also have not burned. We use high-resolution satellite imagery from two complementary sources, PlanetScope and Sentinel-2, to construct a comparable burning measure for all farmers.[11] PlanetScope data is higher frequency (roughly every 2-3 days) so less likely to miss a burning event. This feature is important because burned plots become observationally similar to unburned plots once the soil is tilled for Rabi planting (see Appendix Figure A.4 for an example). Sentinel-2 data are collected at a lower frequency (every week to 10 days) but, unlike PlanetScope, they provide information in the mid-infrared range, which helps separate burned and unburned plots.

We combine monitoring data and spot checks to train a random forest (RF) model with labeled data (burn or no-burn). We conducted spot checks on one randomly selected plot for 50% of farmers in each sample village in November 2019. The spot check protocol was similar to that for monitoring; however, unlike the monitoring visits, spot checks could not be synchronized with the farmer's residue management timing.[12] Our labeled set of 681 plots includes burn labels (positives) from the spot check and monitoring data and no-burn labels (negatives) only from the monitoring data.[13]

[11] PlanetScope has a 3-meter resolution and Sentinel, 20-meter. Other commonly used sensors such as MODIS and VIIRS are available at only lower resolution, 375 meters to 1 kilometer, and therefore inappropriate for the small plots we study.

[12] Other differences were that only one randomly selected plot was visited per farmer and all observation occurred outside of the plot. We did not use spot check data as a primary outcome because to have sufficient statistical power, we would have had to conduct repeated visits, which might have directly affected behavior.

[13] We exclude negative labels collected during spot checks because they indicate no burning in the days

The RF model uses pixel-level data from the two sensors. It outputs a pixel-level continuous prediction score ranging from 0 to 1, which represents the proportion of decision trees that the model classified as burned. We avoid over-fitting by holding out each plot (consisting of many pixels) from the training set, obtaining a prediction for each held-out pixel. To aggregate pixel-level data to a plot-level burning outcome, we average the predicted score across pixels in a plot (omitting perimeter pixels) and then choose a threshold, above which a plot is classified as burned, to maximize overall accuracy of the prediction relative to the plot-level label. To generate binary burn estimates for all plots in the data set, we apply the mean of the trained RF models (recall that we have one trained model for each of the plots in the training set, given the procedure to avoid over-fitting) to unlabeled pixels, aggregate to the plot level, and apply the classification threshold. For consistency with other contract outcomes (a higher value is an environmental improvement), we invert the burning classification when estimating treatment effects. Hence, this farmer-level outcome equals zero if a farmer is predicted to have burned any of his plots. The overall model accuracy is 82% (see Appendix A.5 and Walker et al. (2022) for additional detail on the data, data processing, and machine learning model).

Endline survey In June 2020, we conducted a phone-based endline survey following the Rabi harvest.[14] In addition to agricultural production and income, the survey collected information about residue management decisions, and the importance of cash and trust in those decisions. We use these data to construct measures of take-up of the main alternatives to burning: balers (*ex-situ*) and Happy Seeders (*in-situ*).

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 Appendix Table A.2). The p-value of the joint F-test is 0.48 between treatment

immediately preceding the spot check visit but provide no information about burning outside that window. We test for potential bias from the lack of negative labels in the control group in Appendix A.5 and find no indication of bias.

[14]The contract rollout and monitoring were completed prior to the COVID-19 pandemic. The in-person endline survey, scheduled for April 2020, had to be switched to phone-based.

and control and 0.81 between standard and upfront PES. In each comparison, self-reported burning in 2018 is balanced. We observe slight imbalance for land size and CRM indices in some tests.

We have no attrition for our main outcomes of PES compliance and remotely-sensed burning. Response rates for the endline survey were over 80% (reasonable for a phone survey), but show some differential attrition (see Appendix Table A.3). The treatment group was about 5 percentage points less likely to respond than the control, while the standard and upfront PES arms were equally likely to respond. We show robustness to bounding following Lee (2009) for analysis that relies on endline survey data and pooled treatment effects.[15]

We see no differential attrition across treatment groups by baseline characteristics or by burning outcomes (see Appendix Table A.4).

3 Results

We estimate the following equation:

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

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 is the effect of being assigned to the standard PES treatment, and γ is the effect of assignment to the upfront PES treatment (each relative to the control group).

3.1 Did farmers take up the PES contract offers?

In Figure 1, we examine differences across treatments in whether the surveyor found and offered the farmer a PES contract, as well as whether the farmer was eligible for the offer

[15] Because the randomization was stratified, we trim observations from the control group within strata and include strata fixed effects in the estimation.

(had a bank account and had not yet harvested his paddy). These outcomes are zero by construction in the control group, and they are determined for treatment farmers before they learned the details of the contracts. Farmers were identified and found to be eligible in both treatment arms at a similar rate.

Next we consider program take-up, which is again zero by construction for control farmers. Take-up (whether a farmer signed the PES contract) was high, with around 72% of farmers in both treatment arms signing the contract.[16] Conditional on being found and being eligible, the probability that a farmer took up a contract is around 87%. This is consistent with the contract's high option value in both treatments, because farmers who choose to burn forego the conditional payments but incur no fines. 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 it could be due to farmers not receiving the upfront cash straight away. They were asked for their bank account information, and funds were transferred to them 2-3 days later.

3.2 Did farmers who were offered PES contracts reduce crop residue burning?

In Table 1 we examine treatment impacts on contract compliance, i.e., whether the farmer called for monitoring and no plots were recorded as burned in the monitoring visit(s). Column (1) shows that 8.5% of farmers complied with the contract in the standard PES group. Compliance in the upfront arm is 10 percentage points higher, at 18%, and equality between the two groups can be rejected with $p < 0.01$.[17] Thus, upfront payments make farmers twice as likely to comply with the contract.

Next, we analyze our remote sensing measure of whether a farmer burned any plots. Column (2) shows that relative to the control group, upfront PES increases not-burning by about 8 percentage points, or 85% relative to the status quo. The fact that this effect size is modest in absolute terms (most farmers still burned) is likely related to the payment level

[16]Table A.6 shows that the take-up rate was similar across all sub-treatments.

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

not covering the full (opportunity) cost of CRM equipment rental.

In contrast to what we estimate for upfront PES, the effect of standard PES relative to the control group is indistinguishable from zero. Thus, standard PES payments were entirely inframarginal: the 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.

The effects on not-burning are robust to alternative modeling choices. First, alternative thresholds for classifying burning in the remote sensing model show similar or stronger treatment effects, including a threshold that balances accuracy for burn and no-burn labels (Figure A.5 and Column 1 of Appendix Table A.5). Second, about 18% of the sample had at least one plot predicted to be burned and at least one plot predicted to be not burned. Plot-level treatment effects are of similar magnitude to our main farmer-level result (Column 2 of Appendix Table A.5). Finally, treatment effects estimated on spot check data are similar in magnitude (Column 3 of Appendix Table A.5), but with considerably lower statistical power and a (mechanically) higher control group rate of not burning, given that a one-time plot visit missed some burns.

Though we lack statistical power to test for arm-by-arm differences, we briefly describe the effects of each of the four sub-treatments (see Appendix Table A.6). Paying more in the standard PES variants (₹1,600 versus ₹800) increased the point estimates on compliance and remotely sensed not-burning, though the differences are statistically insignificant. Compliance with the ₹1,600 arm is lower than with either upfront arm. This is striking given that the upfront contract only pays ₹800 per acre. Across the two upfront arms (25% upfront versus 50% upfront), it is theoretically ambiguous which should perform better, as 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 more is paid upfront. Our design does not allow us to test the effect of a higher payment level with a portion paid upfront. Upfront PES with a higher payment level would presumably be more effective, and our cost-benefit analysis in section 4 suggests it would still be cost-effective.

In Columns (3) and (4) of Table 1, we show treatment effects on the main *ex-situ* and *in-situ* alternatives to burning: self-reported baler and Happy Seeder use. Increased use of balers – by 10 percentage points – can explain all of the reduced burning achieved through upfront PES; every farmer who switched away from burning because of the upfront PES program seems to have switched to baling their straw. (The lower and upper Lee bound point estimates are 8.8 and 14.5 percentage points; see Appendix 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 based burning measure, we see no difference in baler or Happy Seeder usage in the standard PES arm relative to the control group.[18]

3.3 Why did upfront payments increase farmer PES compliance?

Upfront PES reduces burning more than standard PES. We hypothesize that two mechanisms, distrust in the conditional payment and liquidity constraints at the time of residue management, 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.[19] In Table 2 we do not find that upfront PES worked differentially better than standard PES either those with high liquidity constraints or high distrust.[20]

We also asked a subset (63%) of farmers in the standard and upfront arms about distrust and financial constraints related to CRM decisions and the PES program in the endline survey.[21] Farmers in the upfront arm are 7 percentage points more likely than farmers in the standard PES arm to state that they trusted that the conditional payment would be made if they complied (see Table 2).[22] In contrast, farmers in the upfront arm expressed a similar

[18]Besides lower costs, two benefits of burning that farmers cite are less delay in sowing the Rabi crop and higher agricultural yields. Upfront payments may also have directly affected agricultural outcomes. We see no effect from either treatment on crop yields for rice or the Rabi crop, or on delays in sowing the Rabi crop (Appendix Table A.8).

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

[20]Like all heterogeneity on observables, this null result could reflect the measures being bad proxies for the construct, being correlated with other factors, or lacking sufficient sample variability to statistically detect an effect.

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

[22]Notably, the higher reported trust in the ex-post payment in the upfront PES arm is not limited to those who actually received that payment; trust is equally high among those who did not comply in this

importance of cash shortages for CRM decision-making to farmers in the standard PES arm. Of course, this does not necessarily imply that upfront payments are unimportant for easing liquidity constraints and enabling CRM equipment use. 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 many farmers.

4 Program Costs and Benefits

Although upfront PES outperforms standard PES in terms of reducing burning, the relative cost-effectiveness is ambiguous because upfront payments occur regardless of compliance. Column (1) of Table 3 shows the treatment effects on contract payments per acre (zero by construction in the control group), which are higher in upfront PES due to higher compliance and to upfront payments to all farmers who took up. To assess cost-effectiveness, we estimate the cost per additional unburned acre by dividing the Column (1) estimates by Column (2) estimates (the not-burning effects shown earlier).[23] (Appendix Figure A.6 shows the results by treatment arm.) The effect of standard PES on burning is small and statistically imprecise. Because upfront PES entails three times as large a payment per acre as standard PES, the cost-effectiveness gap between the contract types is small: Upfront PES costs ₹4050 ($51) per unburned acre, compared to ₹5157 ($64) for standard PES (Column 3).

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, 53.5% of which can be attributed to Kharif burning in Punjab. Estimates of the Value of a Statistical Life (VSL) for India range from $700,000 (Majumder et al., 2018) to $5.6 million (Madheswaran, 2007). Using the lower bound of this range as a conservative

arm. Thus, trust levels in the upfront arm are associated 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 got the payment (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.

[23]We exclude administrative costs (to enroll farmers and monitor compliance) because they are sensitive to program scale and specific protocols used, and they are low relative to payments even with our high-touch protocols. Administrative costs were around ₹480 per enrollee, equivalent to 10% of the cost per unburned acre (based on payments to farmers) in Table 3.

estimate, this implies \$32 billion of annual damages. 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 mortality damages of burning are \$8,000 per acre (₹632,000), which is 150 times the per acre cost of reducing burning through PES with upfront payment. Put differently, the cost of upfront PES was \$4400 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 there is limited state capacity. Our study design and findings highlight the importance of factoring in these same 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 the better performance of contracts with some of the payment given upfront. This insight is not PES-specific and is likely relevant for conditional cash transfer programs, more broadly.

Besides distrust and cash constraints, the modest payment levels no doubt contributed to the lack of impact of the standard PES contract we evaluated. 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 likely 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, so addressing supply constraints is important so that subsidies do not mostly translate into higher equipment rental prices.

But 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 builds up. Similarly, a longer-term PES program might stimulate the development of a market for short-term loans for equipment rental, addressing liquidity constraints and further 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 the cross-jurisdiction externalities, cooperation across jurisdictions or higher-level government action 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.

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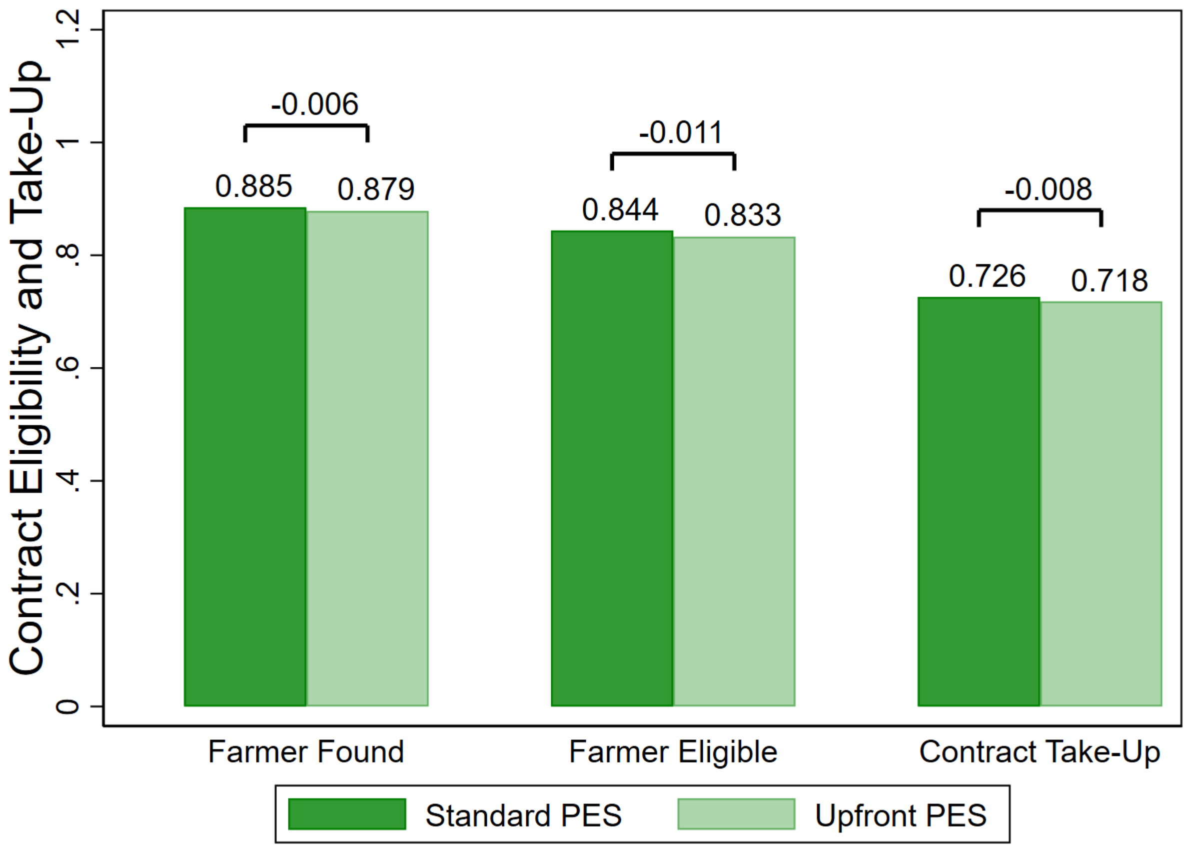
Figure 1: Contract Eligibility and Take-Up



Note: “Farmer Found” takes the value 1 if the respondent was available during the intervention. “Farmer Eligible” takes the value 1 if the respondent was available during the intervention and had a bank account. “Contract Take-Up” takes the value 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.

Table 1: Contract Compliance and Not Burning

	Complied with Contract (1)	Not Burned (2)	CRM techniques: Baler (3)	CRM techniques: Seeder (4)
Standard PES	0.085	0.020	-0.010	-0.020
	(0.015)***	(0.030)	(0.037)	(0.023)
Upfront PES	0.183	0.077	0.096	0.013
	(0.020)***	(0.032)**	(0.039)**	(0.026)
p-val: Standard PES = Upfront PES	0.000	0.071	0.014	0.157
Control mean	0.000	0.091	0.199	0.102
Standard PES mean	0.084	0.098	0.171	0.087
Upfront PES mean	0.185	0.161	0.295	0.112
N	1668	1664	1387	1387

Note: Standard errors in parentheses clustered at the village level. Strata fixed effects included. "Complied with Contract" takes the value 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. "Not Burned" takes the value 1 if the farmer did not burn any of his plots. "Baler" takes the value 1 if the farmer reported in the endline that he used a baler. "Seeder" takes the value 1 if the farmer reported in the endline that he used a Happy Seeder or a Super Happy Seeder. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table 2: Liquidity and Distrust as Moderators of Treatment Effects

Panel A: Liquidity Constraints and Distrust

Outcome variable:	Complied with Contract		Burned (Balanced Accuracy)		Burned (Maximum Accuracy)	
Type of constraint:	Distrust (1)	Liquidity (2)	Distrust (3)	Liquidity (4)	Distrust (5)	Liquidity (6)
Upfront PES	0.114	0.088	0.031	0.030	0.054	0.051
	(0.030)***	(0.029)***	(0.032)	(0.033)	(0.029)*	(0.029)*
Highly constrained	0.030	0.010	0.021	0.007	0.003	0.014
	(0.024)	(0.022)	(0.029)	(0.035)	(0.025)	(0.030)
Upfront PES × Highly constrained	-0.032	0.018	-0.037	-0.032	-0.025	-0.022
	(0.036)	(0.038)	(0.039)	(0.048)	(0.039)	(0.042)
Standard PES mean	0.083	0.084	0.167	0.167	0.104	0.105
Upfront PES mean	0.185	0.185	0.174	0.174	0.143	0.142
N	1172	1182	1168	1178	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: Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Panel A: "Type of constraint" is the heterogeneity variable which is indicated in the second row of the table. "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 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" takes the value 1 if monitoring showed no signs of burning. 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. The comparison group is the standard PES treatment. Panel B: "Trusted Payment" takes value 1 if the respondent trusted that the payment by J-PAL will be made if they did not burn their paddy residue. "Cash Shortage not Important" takes the value 1 if the respondent declared 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. The comparison group is the standard PES treatment. Only those who signed a contract are included in the sample. Both panels: ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table 3: Cost-Effectiveness

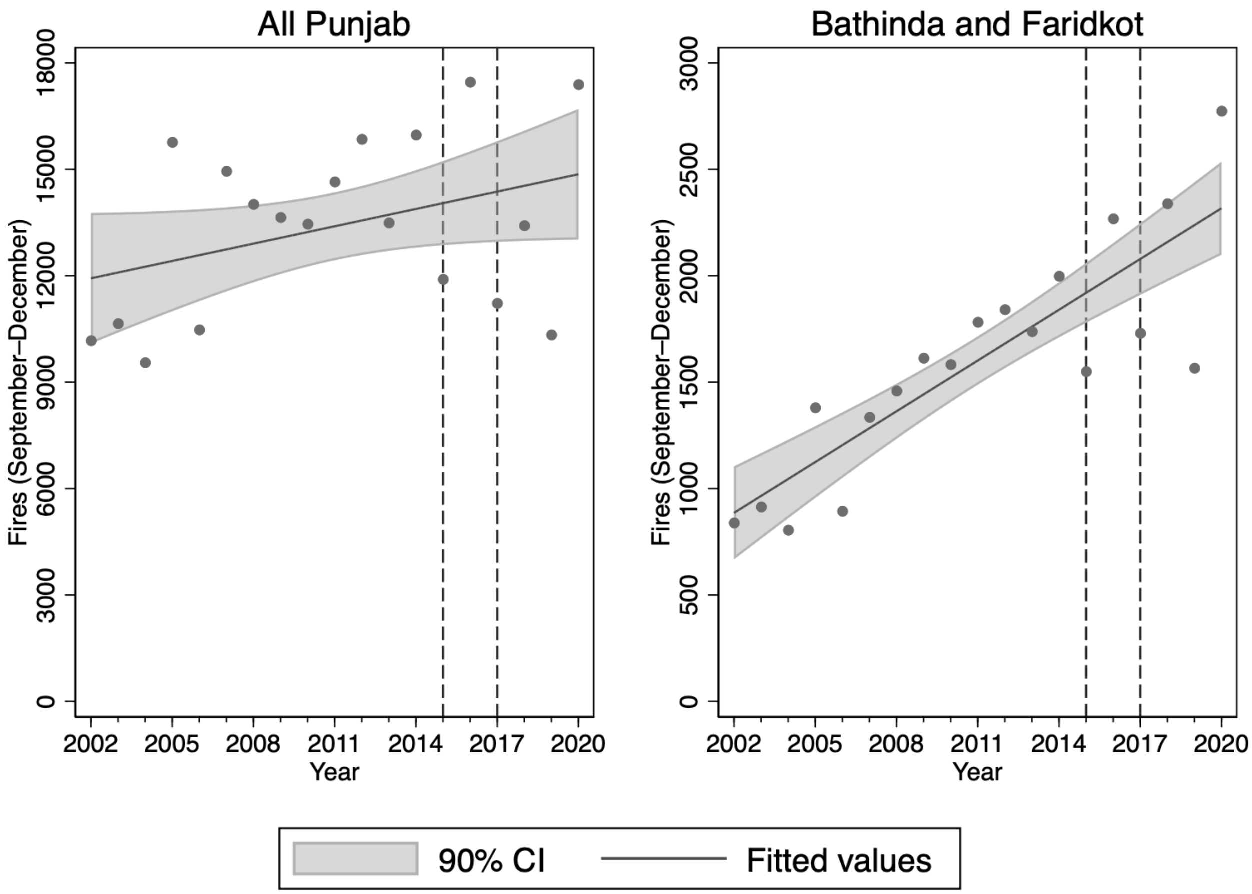
	Amount Paid per Acre (1)	Not Burned (2)	Cost per Unburned Acre (3)
Standard PES	105.6	0.020	5156.5
	(21.7)***	(0.030)	(7156.0)
Upfront PES	310.5	0.077	4051.3
	(15.4)***	(0.032)**	(1595.0)**
p-val: Standard PES = Upfront PES	0.000	0.071	0.864
N	1667	1664	

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. "Not Burned" takes the value 1 if the farmer did not burn any of his plots, and matches the estimates in Table 1. Treatment effects in columns 1 and 2 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 "Not Burned" (column 1 divided by column 2). Standard errors in column 3 are calculated using the delta method. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Online Appendices

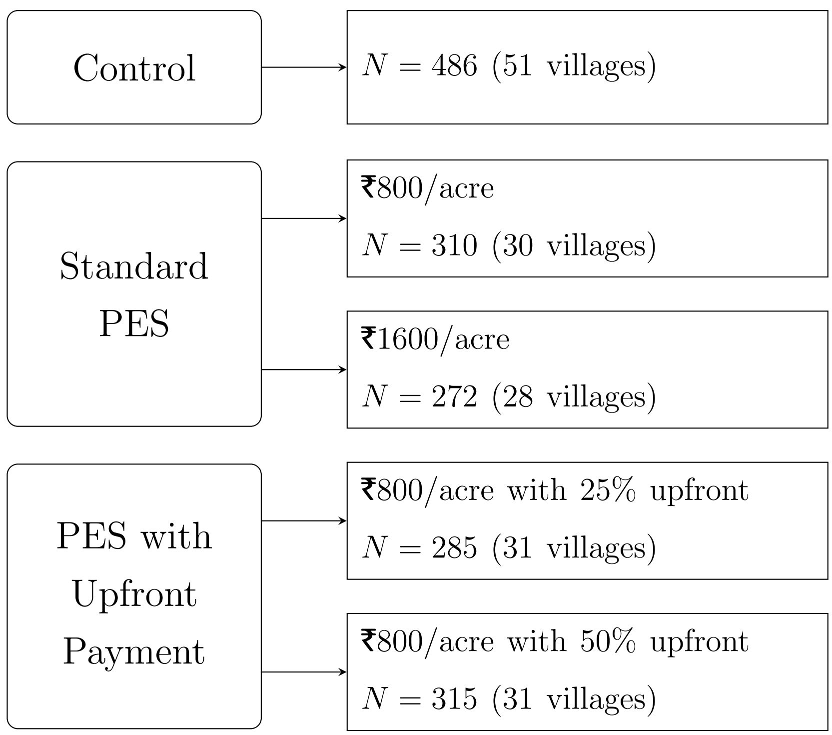
A.1 Tables and Figures

Figure A.1: Time Trends in Fires Based on MODIS Satellite Data



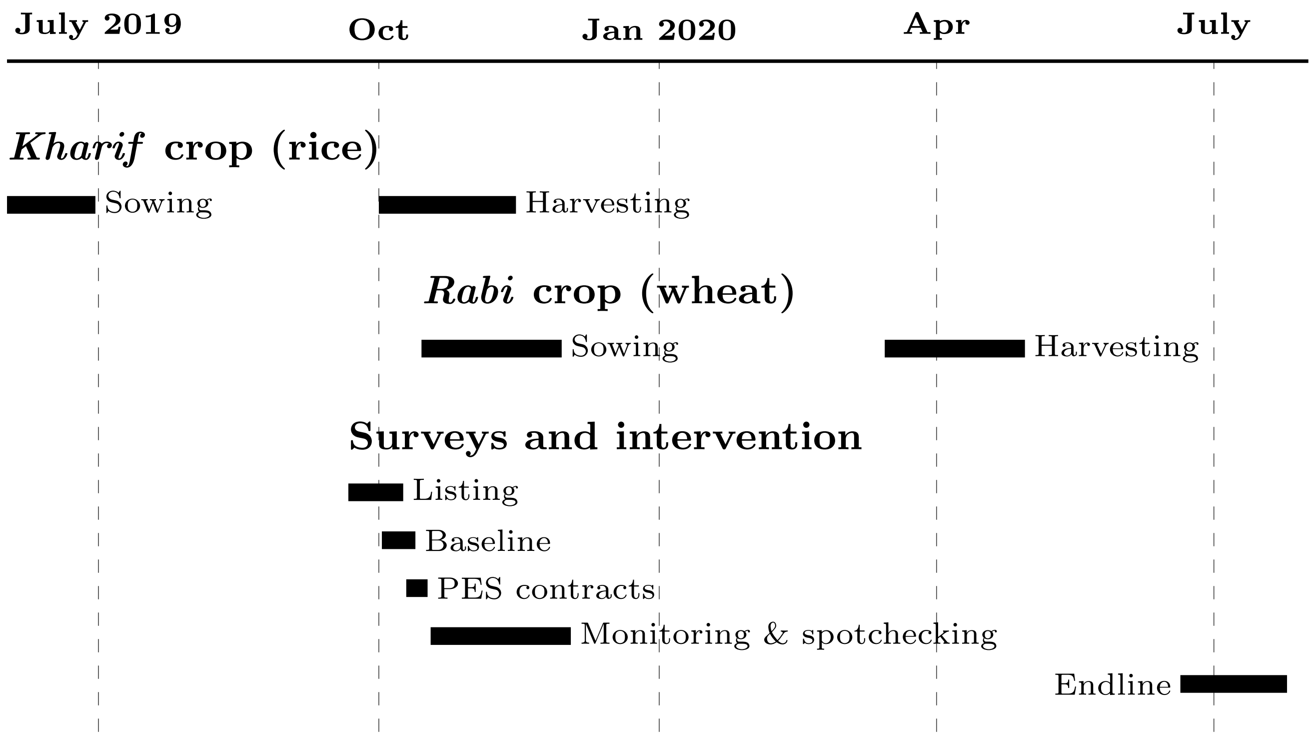
Note: Fire counts from September to December by year, based on MODIS imagery. Left panel shows the state of Punjab; right panel shows study districts. The line at 2015 indicates the introduction of the burning ban; the line at 2017 indicates the introduction of the two-year CRM subsidy.

Figure A.2: Experimental Design



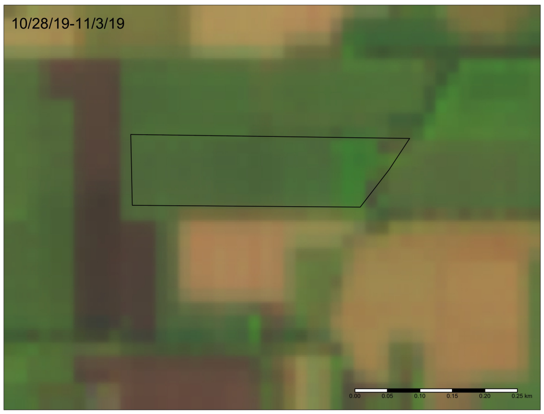
Note: Treatments are assigned at the village level. See text for additional detail.

Figure A.3: Timeline

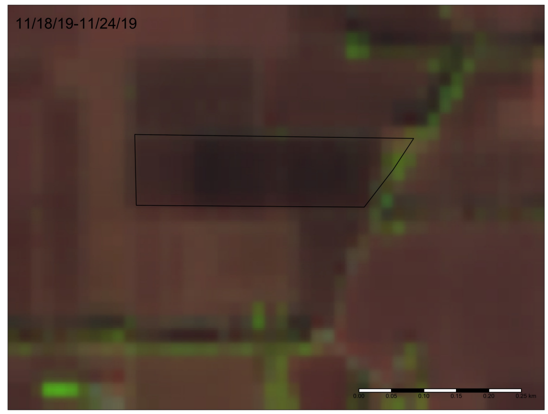


Note: Calendar of agricultural activities and timeline of data collection and implementation.

Figure A.4: Visual Signs of Burning in Imagery: Example



Around harvest time

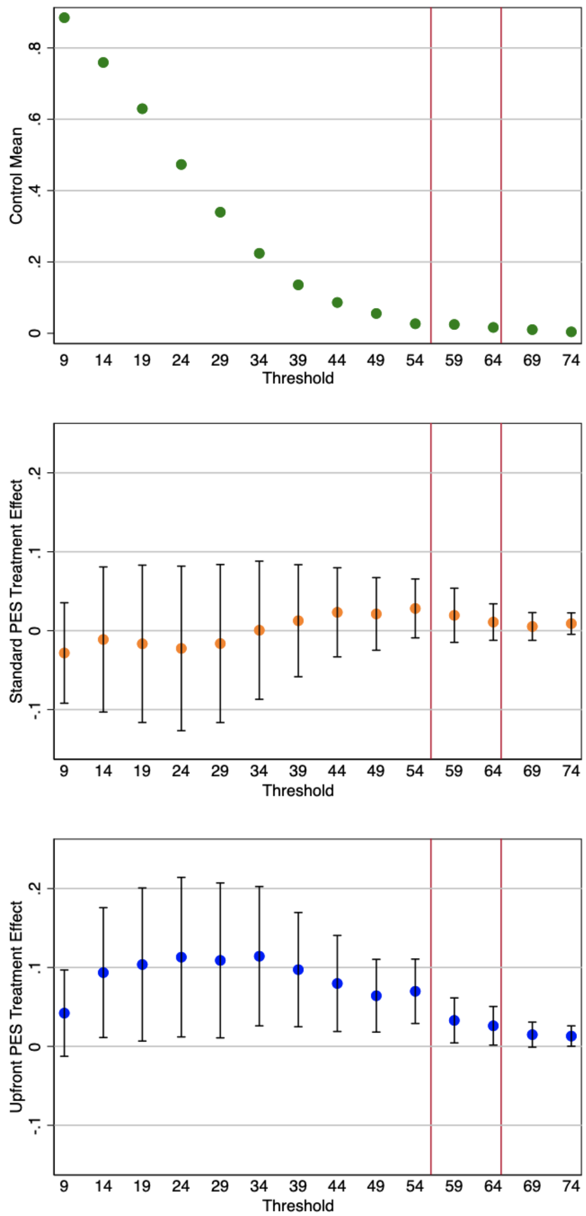


Just after burning

One week after burning

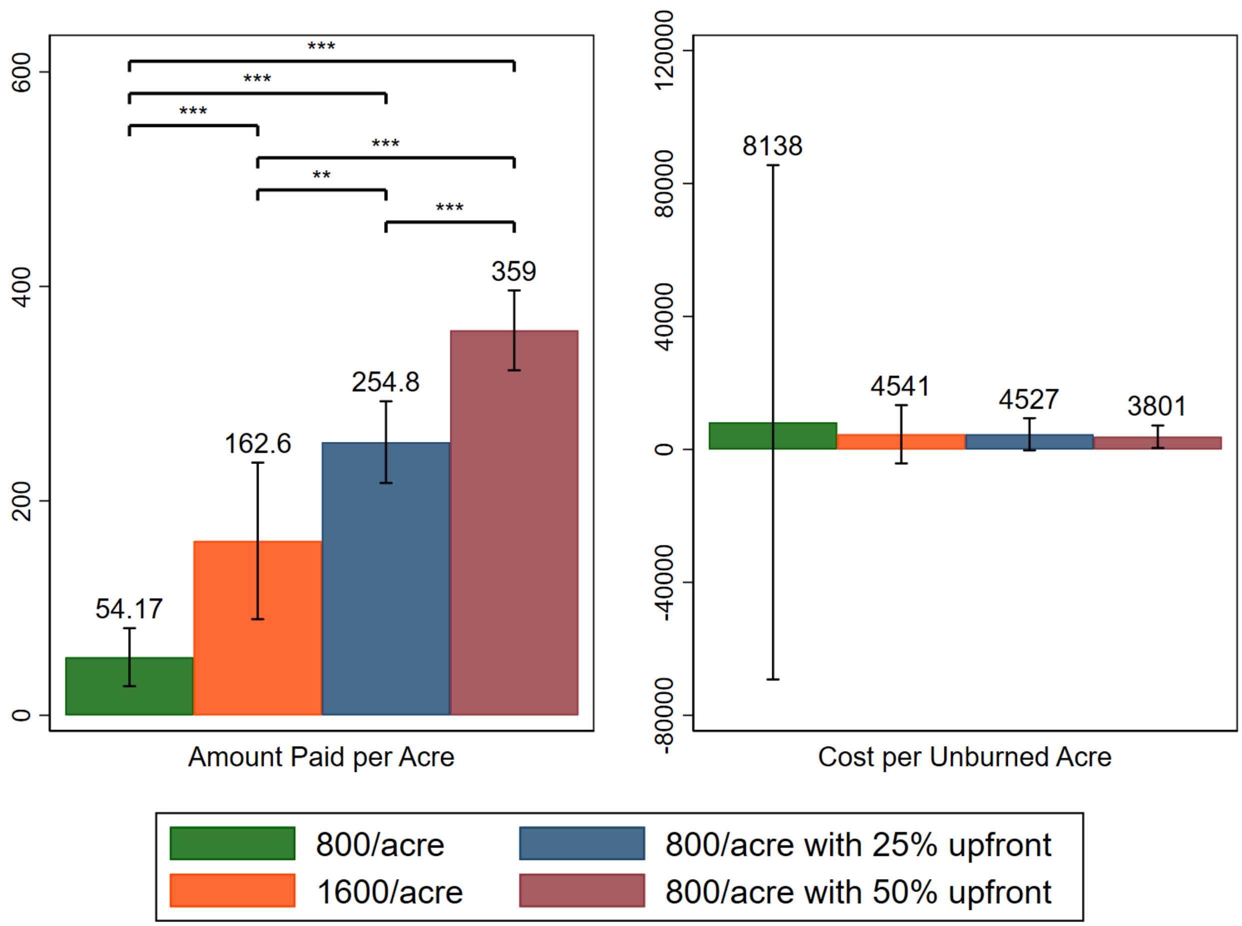
Note: Imagery from Sentinel-2 showing a study plot at different points in the agricultural season.

Figure A.5: 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 not-burning based on different classification thresholds. The classification thresholds are indicated on the x-axis. The binary remote sensing measures of not-burning take value 1 if the farmer did not burn any of his plots. The top graph shows the mean in the control group. The middle graph shows the treatment effects of the Standard PES treatment arm. The bottom graph 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, and that classifies burning to balance type I and type II errors. The remote sensing measure of not-burning with maximum accuracy uses a threshold of 65 while the one with balanced accuracy uses a threshold of 56.

Figure A.6: Cost-Effectiveness by Subtreatment



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 in the left graph are estimated using a modified version of equation (1), which includes indicators for each subtreatment. "Cost per Unburned Acre" is the treatment effect on "Amount Paid per Acre" divided by the treatment effect on "Not Burned". Standard errors in the right graph are calculated using the delta method. Coefficients on top of bars. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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

	Census	Cooperative Members	Study Eligible	Study Enrolled	Diff Coop. - Census	Diff Coop. - Study
	(1)	(2)	(3)	(4)	(5)	(6)
Age (years)	46.79	46.99	46.53	48.34	0.20	1.35
	(14.31)	(14.31)	(14.53)	(12.82)	[0.85]	[0.54]
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)	[0.54]	[0.26]
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)	[0.62]	[0.00]
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)	[0.50]	[0.16]
1(Tried a CRM technique (oth. th. burning))	0.90	0.90	0.85	0.74	-0.00	-0.16*
	(0.30)	(0.31)	(0.36)	(0.45)	[0.89]	[0.04]
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)	[0.20]	[0.10]
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)	[0.80]	[0.57]
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)	[0.68]	[0.91]
Observations	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 of the RCT; column 4 includes the sample of census respondents in the RCT. Columns 1 to 4 are the means in the samples, and columns 5 and 6 are the differences between the means. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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	0.504	0.500	0.011	0.020	0.003	-0.012
				(0.039)	(0.042)	(0.044)	(0.039)
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				0.475	0.482	0.693	0.808

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 3 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). Regressions cluster standard errors at the village level and include strata fixed effects. Income variables relate to income derived in the past 12 months and are measured in ₹1000. Index variables in Panel C are binary. ***(**)(*) indicates significance at the 1%(5%)(10%) 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 group mean	0.130
Standard PES group mean	0.187
Upfront PES group mean	0.182
N	1668

Note: "Attrition" takes the value 1 if the respondent was not in the endline. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level. ***(**)(*) indicates significance at the 1%(5%)(10%) 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.	Financial Const.	Distrust	Info. Const.	Access Const.	Neg. Beliefs	Burned Paddy Residue in 2018	Not Burned (Balanced)	Not Burned (Maximum)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Standard	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096
	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)
Upfront	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033	-0.033
	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)
Het. Var.	-0.001	0.000	0.004	0.037	0.001	0.007	-0.001	0.003	0.004	0.054	-0.002	0.031	0.007	-0.043	-0.021	-0.064	0.212
	(0.003)	(0.003)	(0.004)	(0.036)	(0.001)	(0.003)	(0.002)*	(0.009)	(0.003)	(0.042)	(0.035)	(0.031)	(0.043)	(0.038)	(0.054)	(0.042)	(0.092)
Standard x Het. Var.	0.003	-0.002	-0.011	0.022	0.004	-0.013	-0.000	-0.012	-0.005	0.008	0.060	0.002	-0.049	0.061	0.011	-0.027	-0.127
	(0.005)	(0.004)	(0.007)	(0.055)	(0.002)	(0.004)**	(0.002)***	(0.013)	(0.004)	(0.056)	(0.055)	(0.046)	(0.06)	(0.063)	(0.072)	(0.07)	(0.126)
Upfront x Het. Var.	0.001	0.001	0.003	-0.013	-0.000	-0.008	0.001	-0.003	-0.002	0.024	-0.058	0.019	-0.032	0.031	0.060	0.071	-0.149
	(0.004)	(0.004)	(0.006)	(0.053)	(0.002)	(0.004)	(0.002)*	(0.012)	(0.004)	(0.058)	(0.049)	(0.05)	(0.058)	(0.054)	(0.071)	(0.072)	(0.121)
P-value test Standard x Het. Var. = Upfront x Het. Var.	0.705	0.576	0.066	0.545	0.096	0.060	0.205	0.465	0.401	0.767	0.033	0.736	0.758	0.641	0.457	0.226	0.852
Control group mean	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124
Standard group mean	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192	0.192
Upfront group mean	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180	0.180
N	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112	1112

Note: The outcome is an indicator that takes the value 1 if the respondent attritted from 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” takes the value 1 if the farmer burned paddy residue in 2018 and 0 otherwise. “Not Burned (Balanced)” refers to the remote sensing measure of not-burning using the balanced accuracy threshold, and “Not Burned (Maximum)” refers to the remote sensing measure of not-burning using the max accuracy threshold. Coefficients are estimated using a modified version of equation (1), which includes both a level and treatment interactions for the heterogeneity variable. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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

	Balanced Accuracy (Farmer Level)	Maximum Accuracy (Plot Level)	Spot Check
	(1)	(2)	(3)
Standard PES	0.008	0.022	0.014
	(0.042)	(0.036)	(0.077)
Upfront PES	0.115	0.101	0.105
	(0.042)***	(0.036)***	(0.073)
p-val: Standard PES = Upfront PES	0.008	0.023	0.233
Control group mean	0.202	0.150	0.371
Standard PES mean	0.198	0.154	0.364
Upfront PES mean	0.313	0.265	0.456
N	1664	2875	715

Note: "Balanced Accuracy (Farmer Level)" takes the value 1 if the farmer did not burn any of his plots according to a remote sensing measure that classifies burning to balance type I and type II errors. "Maximum Accuracy (Plot Level)" takes the value 1 if a plot was not burned according to a remote sensing measure that classifies burning to maximize overall model accuracy. "Spot Check" takes the value 1 if a plot showed no sign of burning during a random spot check. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level. Plot level regressions are weighted by the inverse of the number of plots the farmer has. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.6: Treatment Effects Disaggregated by Subtreatment

	Contract Take-Up (1)	Complied with Contract (2)	Not Burned (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" takes the value 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. "Not Burned" takes the value 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 Upfrong 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. ***(**)(*) indicates significance at the 1%(5%)(10%) 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" takes the value 1 if the farmer reported in the endline that he used a baler. "Seeder" takes the value 1 if the farmer reported in the endline that he used a Happy Seeder or a Super Happy Seeder. The second panel shows the Lee bounds for the treatment effects by treatment group. For details on the Lee bounds, see footnote **??**. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

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 second panel shows the Lee bounds for the treatment effects by treatment group. For details on the Lee bounds, see footnote **??**. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.9: 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" takes the value 1 if the monitoring led to the conclusion that the respondent complied with the contract i.e. did not burn his paddy 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. ***(**)(*) indicates significance at the 1%(5%)(10%) level.

Table A.10: Heterogeneity of Treatment Effects on Contract Take-Up

Outcome variable:	Program Take-Up				
Type of constraint:	Liquidity	Distrust	Information	Access	Negative Beliefs about Alternatives
	(1)	(2)	(3)	(4)	(5)
Upfront PES	0.004	-0.018	0.011	-0.014	-0.019
	(0.040)	(0.041)	(0.041)	(0.042)	(0.045)
Highly constrained	0.020	0.024	-0.057	-0.020	-0.041
	(0.036)	(0.042)	(0.047)	(0.030)	(0.046)
Upfront PES × Highly constrained	-0.015	0.035	-0.044	0.015	0.023
	(0.051)	(0.059)	(0.058)	(0.048)	(0.061)
Pooled PES mean	0.734	0.735	0.734	0.735	0.734
N	1182	1172	1182	1168	1182

Note: The row labled "Type of constraint" indicates the heterogeneity variable: "Liquidity" is an index indicating liquidity constraints, including constrained access to cash and loans. "Distrust" is an index indicating the farmer's distrust in categories of people and organizations. "Information" is an index indicating the farmer's lack of knowledge about CRM equipment. "Access" is an index indicating the farmer's difficulties in accessing CRM equipment. "Negative Beliefs about Alternatives" is an index indicating the strength of the farmers 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 or strength of beliefs is larger than or equal to the median. The outcome variable is indicated in the top row of the table: "Program Take-Up" takes the value 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. ***(**)(*) indicates significance at the 1%(5%)(10%) 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

J-PAL
ABDUL LATIF JAMEEL POVERTY ACTION LAB
SOUTH ASIA AT IFMR

${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 ("max 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 max 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.

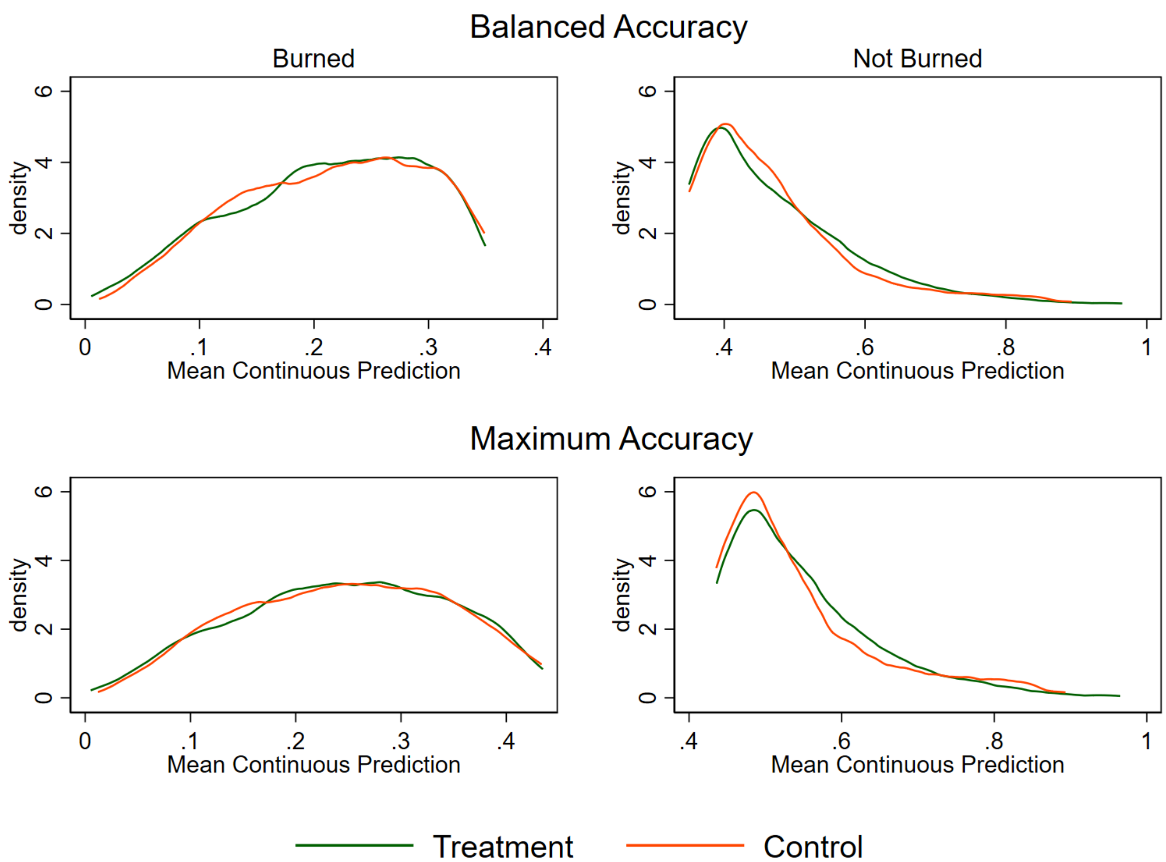
The RF model is trained using negative labels that are only available for the treatment group (and positive labels for both treatment and control groups). This could introduce bias into the classification if the spectral signature of not-burning is affected by treatment; if not-burning looks the same in treatment and control, this is not an issue. As one check on potential bias, Figure A.7 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:	Not Burned	
	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.7: 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.