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

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Abstract

Particulate matter dramatically lowers life expectancy across India, especially in north India. We use a randomized controlled trial in the northern state of Punjab to test the efficacy of conditional cash transfers (i.e., payments for ecosystem services, or PES) in reducing crop residue burning, an important contributor to the region's exceptionally high air pollution burden. Relative to the standard PES contract that makes payments only after compliance is verified, partial upfront payment may increase compliance, because it can help a credit-constrained participant cover the monetary costs of compliance and build trust that the promised conditional payments will be paid. To test this hypothesis, we randomize paying a portion of the transfer upfront and unconditionally. We find that, despite receiving a lower incentive to comply, farmers in contracts with partial upfront payment reduce burning by 8-11 percentage points, significantly more than farmers receiving the standard contract. We also show that offering partial-upfront cash transfers to farmers is a cost-effective way to improve India's air quality.

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1 Introduction

Air pollution lowers the life expectancy of the roughly half billion people living in north India by as much as seven years – arguably, the highest regional health burden from pollution in the world (Lee and Greenstone, 2021). At the same time, key contributors to this pollution burden – industrial and agricultural activities – are vitally important income sources for the region's relatively poor population. Lowering air pollution levels while sustaining economic growth is a central regulatory challenge in India, and across much of the developing world (Duflo et al., 2018; Jayachandran, 2022).

Air pollution associated with crop residue burning is a classic example of this challenge: farmers maximize profits, neglecting environmental externalities from burning. Mechanized rice harvesting increases profits by reducing labor inputs and increasing yields but leaves rice stalk (or stubble) as residue on fields. Controlled burning is the cheapest and fastest way to clear this residue, and most farmers favor this approach over the use of less polluting "crop residue management" (CRM) equipment (Kumar et al., 2015).[1] Today, residue burning is an important contributor to pollution across Asia, including China (Chen et al., 2017), Southeast Asia (Oanh et al., 2018) and South Asia. In north India, smoke from residue burning blankets the agricultural states of Punjab and Haryana at harvest time, and spreads to the urban megalopolis of New Delhi hundreds of miles away, affecting millions of people's health (Cusworth et al., 2018). The Global Burden of Disease Working Group (2018) report attributed 66,000 deaths in India to residue burning in 2015.[2] Residue burning is also an important source of greenhouse gases,s responsible for around 1 percent of annual global emissions (NASA, 2017; Jain et al., 2014; Sarkar et al., 2018; Shindell et al., 2012). Murali et al. (2010) estimates that residue burning in India emits around 4 million metric tons of carbon dioxide equivalents each year.

These social costs of burning far exceed the private profit gains to farmers from choos-

[1] In our baseline survey, farmers report a 7-8 day delay to access a "Happy Seeder" – a state-promoted CRM approach that costs ₹3,000 or around USD 40 per acre to rent and use. Throughout, we refer to non-burning approaches to managing residue (including hiring workers to manually remove it) as CRM.

[2] Indian districts in the top quintile of daily fires have three times the acute respiratory infection risk relative to being in one of the other four quintiles Chakrabarti et al. (2019). Residue burning is also associated with higher infant mortality in Brazil and India (Rangel and Vogl, 2019; Pullabhotla, 2018) and lower student performance in China (Graff Zivin et al., 2020).

ing burning over CRM. Yet, limited state capacity and the political clout of farmers have undermined the efficacy of policies aimed at getting farmers to internalize the externality. Fines for burning are on the books but rarely enforced, and CRM equipment subsidies often do not include farmers' preferred CRM machines and also not reduced end-user rental prices enough. Crop burning remains a pressing policy problem to solve.

We report on a randomized controlled trial (RCT) that evaluates the efficacy of Payments for Ecosystem Services (PES) contracts in reducing residue burning by farmers. By conditioning cash transfers on avoidance of an environmentally harmful behavior – here, burning – PES programs increase the private (opportunity) cost of environmental degradation. By rewarding the outcome, they offer a more flexible incentive for behavior change than equipment (input) subsidies, and by using a carrot rather than a stick, they avoiding the political challenges of fines.

The standard PES contract fully conditions payments on farmer behavior and provides payment once compliance is verified. However, farmer distrust that the contract will be honored can lower the incentive value of the payment. In addition, a lack of cash-on-hand to pay for CRM can lower farmer compliance irrespective of incentive size. Both hurdles might be overcome by offering payment before the farmer needs to undertake the costly behavior. Partial upfront payment can act as a costly signal to increase trust that the conditional payment will be delivered, increasing compliance. It can also help alleviate liquidity constraints. However, in many contexts, upfront payments would be challenging to recoup in the event of non-compliance with the PES contract, resulting in substantial transfers to farmers who continue to burn (or otherwise engage in the environmentally undesirable activity). In addition, holding the total payment fixed, making some of it upfront and (effectively) unconditional lowers the marginal incentive to comply. Hence, the net effect of upfront and unconditional payments is theoretically ambiguous.

Motivated by these observations, a key innovation of our trial was to randomize PES contract type across three farmer groups: (1) farmers receiving no contract group (control), (2) farmers receiving a contract with payment after verification that the farmer did not burn conditional on not burning (standard PES) and (3) farmers receiving a contract with partial

payment upfront and (explicitly) unconditional on verification (upfront PES).[3]

We implemented the trial during the 2019 rice growing season across 171 villages in the north Indian state of Punjab. Take-up of both standard and upfront PES contracts was similar and relatively high (72%). (Throughout, we report intention-to-treat estimates). Our key finding is that, despite lower marginal payments to comply, upfront PES increased contract compliance by about 10 percentage points, doubling compliance rates relative to standard PES. Contract compliance outcomes are consistent with remote-sensing based estimates of burning, which again show a roughly 10 percentage point increase in the probability that a farmer did not burn. The remote sensing based outcome allows us to compare burning outcomes with the control group, which shows that the payments in the standard PES treatment were inframarginal (i.e., paid to farmers who would not have burned, regardless of treatment). The treatment effect in the upfront PES treatment corresponds to a 50-80% higher rate of not-burning than either the control group or standard PES treatment. Consistent with this result, in our endline survey, farmers in the upfront treatment arm are 9.5 percentage points more likely to report using balers – a piece of CRM equipment used to bundle residue that has been removed from the field – than those in the control group. Farmers offered the standard PES contract do not report any increase in CRM use, again suggestive of no reduction in burning relative to the control group.

Why were partial upfront contracts more effective that standard PES contracts? An analysis of heterogeneous treatment effects by (pre-specified) baseline measures of liquidity constraints and distrust shows no differential treatment effects. It is possible that these measures are imperfect proxies of the relevant individual characteristics. Therefore, we also analyze direct statements provided by farmers in the endline survey regarding the role of cash constraints and trust in determining their CRM decision-making and response to the PES program. We find some evidence that assignment to the upfront PES treatment led to higher trust that contract payments would be made.[4] The majority of farmers also reported that cash on hand affects CRM decisions, at a rate unaffected by treatment.

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

[4]If PES contracts were implemented as policy, repeated implementation might eventually address distrust in payments, making standard PES more cost effective over time.

Finally, we calculate program cost effectiveness, using the remote-sensing outcome to calculate acres of averted burning due to the contract. Standard PES was not cost-effective, simply because it had no impact on burning. Upfront PES was effective at reducing burning, but its cost-effectiveness needs to account for the fact that many treated farmers received the upfront payment but did not comply. For this reason, the cost per averted acre of burning (₹2000 or USD 29) exceeded the total payment for complying (₹800 per acre). Nonetheless, this cost is drastically lower than the benefits of averting an acre of burning. Our back-of-the-envelope estimate of the per acre mortality costs of burning is over ₹350,000. This excludes many other benefits of reducing burning such as reduced morbidity, higher labor productivity, and reduced greenhouse gas emissions.

As a benchmark, we compare the abatement costs for reducing crop burning via PES to those in another high-polluting sector in India, coal-fired power plants. Abatement in coal-fired power plants (the installation of desulphurization scrubbers) also has benefits that exceed costs; however, the benefit-cost ratio is more than ten times greater for residue burning. In particular, the cost per life saved from installing scrubbers in coal-fired power plants is roughly $400,000 versus $3,617 for upfront PES.

The paper is related to several literatures. First, multiple papers highlight the importance of contract design for agricultural decisions and outcomes, such as microfinance and crop insurance (Carter et al., 2017). These include varying aspects such as the timing of when the insurance or loan contract is offered (Burke et al., 2019; Fink et al., 2020; Casaburi and Willis, 2018), and bundling loan offers for risky technologies with insurance (Giné and Yang, 2009). Our contribution is to highlight the importance of contract design for environmental programs.

Second, conditional cash transfers are widely used to improve targeted outcomes, though recent work tests the role of conditionality for take up and outcomes (Baird et al., 2011; Akresh et al., 2013; Attanasio et al., 2015; Aker and Jack, 2021). In contrast to studies that vary conditionality of the payment, we focus on payment timing and show that partial upfront payment during enrollment can improve compliance with a conditional contract.[5]

[5]Evidence from other settings supports the notion that the timing of transfers can affect program outcomes, because of liquidity (Coffman et al., 2019) or other channels.

Third, while PES is widely used and studied, causal estimates of the impact of PES, and especially comparisons of alternative PES program designs, are relatively scarce.[6] Exceptions include Jayachandran et al. (2017), who find that a PES program successfully reduced deforestation in Uganda, Edwards et al. (2020), who find no impact of community-level payments on forest fire prevention, and Jack (2013) and Oliva et al. (2020), who show that program design affects the cost effectiveness of afforestation contracts. We contribute with an evaluation of the impact of alternative contract structures on efficacy and cost-effectiveness in a novel setting. PES programs have been used to address environmental externalities from land use, such as deforestation, but have rarely been applied to crop residue burning, a major source of both local and global pollution.

Finally, a growing literature investigates the causes and consequences of crop residue burning (Behrer, 2019; Garg et al., 2021; Pullabhotla, 2018; Graff Zivin et al., 2020; Rangel and Vogl, 2019). Few papers test policy interventions to reduce burning; an exception is Edwards et al. (2020), who experimentally evaluate a bundled intervention of community-level training and large payments to village governments for prevention of forest fires in Indonesia, but find no impact. In India, Kramer and Ceballos (2018) find that conditioning agricultural insurance payouts on not-burning lowers rates of burning, but also lowers insurance coverage. We conduct the first prospective trial of an intervention designed to directly target the opportunity cost of crop residue burning, and show the importance of contract design in the efficacy of such programs. We leverage novel data from a new remote sensing model to measure crop residue burning (see Walker et al. (2022) for further detail), which is better suited to detecting plot-level changes in burning than existing measures of active fires, burn scars or smoke (Balboni et al., 2021; Behrer, 2019; Edwards et al., 2020; Rangel and Vogl, 2019; Jayachandran, 2009).[7]

[6] PES payments comprise over $ 30 billion in payments (Salzman et al., 2018).

[7] Publications in the remote sensing literature also measure fires using satellite imagery, and have historically relied on coarse resolution sensors, such as MODIS, which offer high frequency but low spatial resolution (e.g., Vadrevu et al. (2011); Liu et al. (2019)). Newer sensors offer higher spatial resolution but less frequent observation, which potentially misses some crop residue fires due to their short visual signature (e.g., Badarinath et al. (2006); Singh et al. (2021)). We add high temporal and spatial resolution imagery from Planet Labs to overcome this tradeoff. See Walker et al. (2022) for additional detail and discussion of the contribution to the remote sensing literature.

2 Background and context

2.1 Crop residue burning

Roughly 80% of the cropped area in the Indian state of Punjab – often described as the granary of India – is cultivated under an annual rice-wheat dual crop system. (Rice is cultivated from June to October (Kharif season), followed by wheat from November to April (Rabi season).) The advent of mechanized harvesting in the 1980s made the dual-crop system more feasible but also created the need to manage the residue that it leaves on the field: mechanized rice harvesting generates over 2.5 tons of residue per acre of rice (Jain et al., 2014). Over time, residue burning has emerged as the main way that Punjabi farmers manage this process. Using satellite imagery spanning 2000-2018 (Distributed Active Archive Center, 2018), Appendix Figure A.1 shows a rising incidence of fires across Punjab as a whole, and in our two study districts of Bathinda and Faridkot.[8] In our listing survey of farming co-operative members in these two districts, *all* farmers reported using a combination of mechanized harvesting techniques that create a need for residue removal.

2.2 Policy responses to residue burning

Recognizing the negative pollution externalities from residue burning, the Indian Penal Code considers residue burning a punishable crime (Section 188). In 2015, a court ruling explicitly banned residue burning and directed north Indian state governments to fine farmers who burned residue, with fines ranging from ₹2,500 to ₹15,000, depending on farmers' landholdings (Bhuvaneshwari et al., 2019; National Green Tribunal, 2015).[9] However, in the face of strong opposition by the farmer lobby and low regulatory capacity for enforcement, penalty-based policies have had limited impact.

In 2017, the central government announced a two-year $144.3 million program covering three states – Punjab, Haryana, and Uttar Pradesh – that sought to reduce residue burning by subsidizing *in-situ* crop residue management alternatives. *In-situ* techniques leave the residue on the field, either pulling up and mulching the stalk or leaving it standing. The

[8] Primary crops in these districts are rice and wheat (Faridkot), and rice, wheat, and cotton (Bathinda).
[9] The National Green Tribunal ruling applied to Rajasthan, Uttar Pradesh, Haryana, and Punjab.

funds were used to subsidize equipment including a new seeding machine, the Happy Seeder, which sows directly through the paddy residue, and the Super Straw Management System, which cuts and chops the residue.[10] The subsidy did not cover *ex-situ* equipment. which remove the residue from the field altogether – for instance, using equipment (or labor) to pull up and gather the straw, and then using another piece of equipment (a baler) to bundle it into bales.

In our baseline survey, similar numbers of farmers (58%) reported being aware of CRM alternatives to burning, and having used these alternatives. Less than a third (32.7%) reported being aware of the government's CRM equipment subsidy, and among those who knew about the scheme, only 10% had applied.[11] Even after the subsidy, the cost of CRM equipment purchase (₹40,000 (USD 570) for a Happy Seeder after the 50 percent subsidy) and rental (up to ₹3,000 per acre for a Happy Seeder, according to our baseline survey data) remain high. Financial outlays are not the only costs associated with these alternatives. Farmers also reported that renting CRM equipment from a co-operative or custom hiring center would take around a week during peak season, potentially delaying Rabi sowing. In addition, the majority of farmers in the baseline survey who were familiar with CRM alternatives raised concerns about negative impacts on agricultural productivity.

State and central government policy approaches to combat residue burning have, to date, been largely ineffective. Fines increase the expected cost of burning, leaving it up to the farmer to choose an alternative to burning. However, without enforcement – which is undermined by political constraints – they are ineffective. Subsidies on CRM equipment are designed to decrease the cost of alternatives to burning, but give the farmer little flexibility if the subsidized alternative is not available or remains more costly than burning – which appears to be the case for government-subsidized CRM. This motivates our focus on an alternative that provides the flexibility and incentives of a fine without some of the political pitfalls: subsidizing not-burning through payments for ecosystem services (PES).

[10] In Punjab, farmers were eligible for a 50% subsidy as individuals or 80% for a 'custom hiring center' or other group to invest in the equipment and rent them out. Agricultural co-operatives were also eligible for an 80% subsidy.

[11] Less than a quarter of the sample reported owning any CRM equipment (note that some of these machines, such as a rotavator, are also used for farm operations other than CRM, e.g., tilling). Farmers largely rent in CRM equipment.

PES programs, while extensively used for several land use outcomes, have not been applied to crop residue burning.[12] In most PES programs, including the one we study, participation is voluntary with non-compliance only penalized through non-payment. This raises two challenges for cost effectiveness. First, farmers who comply may have undertaken the desired activity even absent the contract, i.e. are inframarginal (Alpizar et al., 2007; Alix-Garcia et al., 2012; Burke, 2016; Pattanayak et al., 2020). Second, because of the lack of penalty for non-compliance, many farmers may enroll and later renege, increasing implementation costs whenever there are any fixed administrative or other costs associated with issuing contracts (Oliva et al., 2020).

3 Study design and implementation

We experimentally evaluate the effectiveness of alternative PES contract designs in reducing stubble burning, relative to a status quo (of unenforced fines and insufficient equipment subsidies) control group. The latter allows us to measure the "additionality" and cost effectiveness of alternative PES contracts.

3.1 PES contract design

Our first treatment implements a standard PES contract, with payments conditional on observed outcomes – in our case not burning and paid after compliance is verified. (We discuss how contracts are monitored and enforced below.) We selected the payment level in consultation with the Punjab government, which recommended ₹800 per acre. This constitutes our base contract.

To change behavior, the payment needs to cover the marginal cost of CRM relative to burning, not full cost. Burning might take time or require some material inputs, and some farmers might perceive it as worse for their soil fertility, for example. The fact that not all farmers burn in the status quo (11-21% did not burn in our control group) points to

[12] As discussed in the introduction, the closest applications to our own are Edwards et al. (2020), who offer payments to communities in Indonesia conditional on forest fire prevention, and Kramer and Ceballos (2018), who bundle crop insurance and encouragement to not burn in India by making not burning a condition to receive an insurance payout.

heterogeneity in farmers' reservation price to switch away from burning; some farmers have a negative reservation price, but the vast majority have a positive reservation price, which likely varies considerably. To evaluate the importance of payment levels, we introduce a variant on the standard PES contract, which offers twice the amount of the base contract, or ₹1600 per acre not burned.[13]

We designed a second treatment arm to address important constraints in our study context that might undermine the effectiveness of standard PES contracts. Standard PES contracts pay out only after the desired behavior or action (i.e., not burning) has occurred. Farmers may not undertake a costly action in expectation of a future payment if they do not trust the principal to follow through with the payment or if they lack cash on hand. In our study setting, both distrust and liquidity constraints are plausible barriers to compliance.[14] At baseline only 13% of farmers said they had complete trust in the government, with even lower levels of trust, about 7%, in NGOs. Less than half of the sample had ₹5,000 in savings and the majority said that it would be somewhat difficult or difficult to access a ₹5,000 loan. We therefore introduced a treatment that offered partial payment upfront, with the remainder paid conditional on contract outcomes. The sum of the (potential) upfront and ex post payments was held fixed at ₹800 to match our base contract.

While, in theory, upfront payments could be conditional and recouped from a participant who does not end up complying, in practice, recouping money is challenging (e.g., because participants are poor). Thus, in our contracts, we explicitly made the upfront payment unconditional. Putting this all together, upfront payments have the potential to improve compliance if distrust or liquidity constraints are important barriers, but they might also be less effective or cost-effective. First, with an upfront unconditional component, the conditional payment is lower, which dampens the incentive to comply. Second, the unconditionality

[13]In November 2019, (post roll out of our intervention) the federal court directed the Punjab government to provide farmers ₹100 per quintal of paddy, or about ₹2,500 per acre, conditional on not burning. Concerns about the veracity of farmer's self-declarations that they did not burn led to the program being suspended just a few weeks later. In our endline survey, about 30% of the sample were aware of the government program, of which about half reported applying to the program. The other half reported they learnt of the program only after they had begun residue management. Consistent with it being a low trust environment, 80% of farmers who were aware of the program said they had not anticipate timely PES payments.

[14]Note that these are also likely barriers to the success of other conditional cash transfer programs in other low trust and low income settings.

of the upfront payment may result in substantial payments to non-compliant farmers. We evaluate two variants of this upfront PES treatment, which take the base contract of ₹800 per acre and vary the share paid upfront.

To summarize, we compare the following treatments to a control group:

- Standard PES: Payment of ₹800 per acre conditional on verified absence of burning
- Standard PES: Payment of ₹1600 per acre conditional on verified absence of burning
- Upfront PES: Payment of ₹800 per acre; 25 percent upfront and unconditional, and 75 percent conditional on verified absence of burning
- Upfront PES: Payment of ₹800 per acre; 50 percent upfront and unconditional, and 50 percent conditional on verified absence of burning

3.2 Contract implementation

Eligibility for the study required that a farmer cultivate between 2 and 12 acres of paddy, were planning to harvest after the second week in October and plant the winter (Rabi) crop, and reported using farm equipment that was indicative of burning (namely, used a reaper or did not use a chopper) in the previous year. (The last criterion means that our sample has higher burning than average; by reducing inframarginal payments, this choice allowed us to increase the statistical power to detect changes, given our budget.)

All farmers who participated in the baseline survey met the above criteria. Eligible farmers in treatment villages received a follow-up visit and were offered a PES contract, 5.6 days after the baseline survey, on average. If they could not be located or lacked a bank account, then they were screened out at the contract offer stage.[15]

As part of the contract offer, farmers were first given a basic program description (see Appendix A.2). Interested farmers were then shown the contract (offered by J-PAL) corresponding to their treatment arm, and the enumerator read the terms aloud.[16] Farmers who agreed to the contract terms received an information handout with further explanation

[15]Contract payments were made by electronic transfer, and account information was collected only from farmers in the treatment groups. Only six farmers were screened out due to this criteria.

[16]A sample contract for the ₹800/acre arm with no upfront payments is included in Appendix C.

of the terms and conditions including procedures around monitoring and verifying burning outcomes. During the enrollment visit, enumerators recorded whether the farmer was offered the PES contract in-person and, if not, the reason (e.g., household could be found, no bank account), and whether he took up the contract. A farmer's entire paddy acreage (as physically measured by the surveyors at baseline) was automatically enrolled if the farmer took up the contract. The maximum that a farmer could be paid under the contract was capped at ₹16,000 for farmers in the ₹1600 per acre arm and ₹8,000 in the other treatment arms.[17] Farmers in the upfront PES arm received the upfront portion of their payment 2-3 days after enrollment, via direct bank deposit.

Contract monitoring and enforcement required verification that none of the paddy plots were burnt; any burning was a violation of the contract. Detecting burning or its absence required that project enumerators visit the plot in the short window between when the farmer removed the stubble (by burning or CRM) and when the farmer tilled the soil for planting the Rabi crop.[18] Because of the need to monitor during this farmer-specific window of a few days, the farmer was responsible for calling J-PAL to request monitoring after managing residue and at least four days before sowing his or her Rabi crop.[19] Up to two monitoring visits could be requested if, for example, different plots had different sowing schedules. When farmers called in, appointments were scheduled for monitoring, and the map of all study plots collected at baseline given to the monitor. In the third week of October, farmers who had not already called for monitoring were contacted with a reminder that it was the farmer's responsibility to call in for monitoring.

The monitoring protocol required that the enumerator observe and record multiple observations on each plot, including signs of burnt straw or residue, grey or black ash on the soil, burnt root residue, burnt grass or weeds on the plot boundaries, and burnt leaves or tree branches on the plot boundary. At each plot, enumerators were instructed to inspect the plot perimeter and to walk onto the plot and inspect the soil. In-person visual inspection in

[17]Farmers eligible for the study cultivated 12 or fewer acres of paddy. For farmers with more than 10 acres of paddy, about 7% of the sample, the value of the contract per acre is constrained by the cap.

[18]Prior to the completion of CRM, a monitoring visit could not rule out future burning. After tilling, visual signs of burning become less obvious.

[19]Placing the onus for monitoring on the farmer may lower compliance. However, it increases monitoring accuracy since the precise timing for verifying absence of burning varies from mid-October to late November.

the appropriate time window gives a very accurate indication of whether a field was burned. Upon completion of monitoring, farmers were not immediately informed of the monitoring outcomes. Further, monitoring staff were unaware of how distinct observations would be used to determine contract compliance. The observations were combined into a single farmer-level compliance measure, and payments occurred on a rolling basis upon verification of compliance, about 2-3 days after monitoring. Any signs of burning were considered a contract violation.

3.3 Sample and randomization

We chose our two study districts – Bathinda and Faridkot – because both experience high rates of burning and had little activity to encourage CRM adoption by other organizations.[20] Our sample frame was restricted to villages with functioning farmer cooperatives, and, within these villages, to farmers listed as cooperative members (as of August 2019). Out of 393 villages in our sample frame, we chose the 300 villages with the largest number of members for a phone survey.

We used the phone survey as the basis for initial eligibility screening. We then selected 176 villages with at least 18 eligible households for an in-person baseline survey.[21] Villages with fewer than six completed baseline surveys were eliminated, for a final sample of 171 villages and 1668 respondents. On average, 9.8 farmers per village were enrolled in the study, which is a very small share of the population. This means we are unable to detect impacts on village-level outcomes such as air quality.

We randomly assigned villages to one of four treatment arms (described above) and a control group. Figure 1 summarizes the sample size per treatment arm. Randomization occurred while the listing and baseline surveys were ongoing.[22]

[20] According to the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite data (Distributed Active Archive Center, 2018), Faridkot had about 1.9 fires per square km in 2018, ranking sixth highest in the state, while Bathinda had 1.7 fires per sq km, ranking ninth. VIIRS is a satellite instrument that can be used to detect active fires.

[21] The baseline prioritized villages with the largest number of eligible households based on the listing data. Baseline data collection stopped once the target sample of 176 villages was reached (189 villages fulfilled the criteria above). During the baseline survey, households were re-asked the eligibility questions at the start of the survey. Enumerators moved down a randomly ordered eligible list until 16 surveys were completed or the list was exhausted.

[22] Initial assignment was stratified on (1) district, (2) below versus above median number of eligible house-

To assess sample representativeness, we conducted a census in four study villages in February 2020. 70% of farmers reported being co-operative members. Census farmers, like study farmers, were nearly universally engaged in paddy-wheat cultivation. Reflecting our restricting enrollment to farmers cultivating 12 acres or less (a criterion that 80% of census farmers met), study farmers cultivated less land than census farmers (5.3 acres vs 7.7 acres). Study farmers were 29 percentage points less likely to report knowledge of alternatives to burning and 30 percentage points less likely to report having tried an alternative than were census farmers. This may reflect the smaller landholdings for study farmers.

3.4 Data

Figure 2 presents the the agricultural season for the paddy-wheat cropping cycle in Punjab and the timeline for data collection.

A. Survey data

Baseline survey In October 2019, we conducted baseline surveys with the identified person on the co-operative member list. For over 90% of households, this person was responsible for household agricultural decisions. We collected data on demographics, agricultural production, income and credit constraints, trust in organizations, and barriers to crop residue management. Farmers listed all plots where paddy was being cultivated, and accompanied the enumerator to each of the plots to collect perimeter measures. At each plot, the enumerator used a mapping application on a GPS-enabled tablet and walked the perimeter of the field. The resulting polygons form the basis for monitoring treatment farmers' compliance with the contract and for linking satellite imagery to farmers in both the treatment and control groups. The plot measurement was conducted during the baseline survey, so before farmers learned their treatment status. Thus, any measurement error in plot inventories or

holds based on the phone listing survey, (3) whether baseline survey had been completed in the village, and (4) whether listing survey had been completed in the village. We include a fifth strata that consists of 15 villages that were randomly added to the different arms to supplement the sample size. These were villages in which listing survey had been covered for fewer than 18 but more than six households. The order of listing was randomized, and the baseline and treatment implementation followed the order of the listing. Enumerators for the baseline survey were unaware of a village's treatment status.

field perimeters should be orthogonal to treatment.[23]

Endline survey In June 2020, following completion of the Rabi harvest, we conducted a phone-based endline survey.[24] The survey collected data on self-reported field burning and crop residue management techniques used. We also collected data on agricultural production and income in the last two seasons (Kharif 2019 and Rabi 2020). Attrition between the baseline and endline surveys and balance tests are described in Section 4.1.

B. Contract take-up and compliance data

Contract take-up data At the time of the contract offer, we record the farmer's enrollment decision and in case of non-enrollment reason for refusal. These reasons include not being found during the visit, not having a bank account, or preferring not to enroll.

Monitoring data We record whether a treated farmer called for monitoring. For those that did, we observe monitoring outcomes, including the distinct plot-level signs of burning described above. These were aggregated to a single binary burning outcome. For a farmer to be compliant with the contract, none of his or her plots could show signs of burning. In total, 187 farmers and 319 plots were monitored.

Spot check data In all sample villages we selected one field at random for 50% of farmers for spot checks. The protocol for spot checks was similar to that for monitoring with a few exceptions. First, only one randomly selected plot was visited per farmer. Second, because the farmer did not accompany the enumerator, all observation was conducted from outside of the field. Third, unlike the monitoring visits that occurred when the farmer informed us they had removed their stubble and not yet tilled the soil for their Rabi crop, the spot checks could not be synchronized with the farmer's specific harvest and burning-or-residue

[23]We drop 47 fields (1.6 percent) where either the field ID was missing from the geospatial data or where two fields were completely overlapping.

[24]The was completed prior to the onset of the COVID-19pandemic. However, the in-person endline survey, which had been planned for April 2020, had to be transitioned to be phone-based (this survey attempted to reach respondents a maximum of eight times).

management timing.[25] Overall, we conducted 720 spot checks in November 2019 and spot check data was used as training data for our remote sensing model.

C. Remote sensing data

Satellite data The monitoring data are informative of how many people enrolled in the contract and were verified as not burning, but not the rate of burning among those who were not monitored. Some farmers in the control group might not have burned, and some farmers in the treatment group who did not enroll or did not call for monitoring might also not have burned. Thus, our analysis also uses a measure of burning constructed from high-resolution satellite imagery from two satellite sources, PlanetScope and Sentinel-2.[26] PlanetScope data are higher frequency (roughly every 2-3 days) and less likely to miss a burning event. This feature is important since burnt fields become observationally similar to unburned fields once the soil is tilled for Rabi planting.[27] The lack of persistent visual signature of burning is particularly problematic in the visual and near-infrared bands measured by PlanetScope. Sentinel-2 data are lower frequency (every week to 10 days) but, unlike PlanetScope, provide information in the mid-infrared range, which helps separate burned from unburned fields. Thus, imagery from the two sensors can complement one another.

Data processing and classification We use pixel-level data from the two sensors to train a a random forest (RF) model using binary field-level labels (i.e., whether a field was burned or not) from the monitoring and spot check data (see Walker et al. (2022) for additional detail on the data processing and machine learning model). These ground-measured labels are available at the field- rather than pixel-level. Our labeled set (of 705 labeled fields) includes burn labels (positives) from the spot check and monitoring data and no-burn labels (negatives) only from the monitoring data.[28] The RF model outputs a pixel-level continuous

[25] We did not use spot check data as an outcome because to have sufficient statistical power, we would have had to have conducted them for many more farmers, with repeat visits due to this timing issue.

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

[27] Appendix Figure A.2 shows an example of this in Sentinel-2 imagery for one study field.

[28] We exclude negative labels collected during spot checks because they indicate a lack of burning in the days immediately preceding the spot check visit but provide no information about burning outside of that window leading up to the visit.

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 field from the training set, obtaining a prediction for each hold-out pixel in the labeled set.

To aggregate from pixel-level data to a field-level burning outcome, we average the score across pixels in a field (omitting perimeter pixels) and then choose a threshold above which a field is classified as burned. We present two alternative thresholds: (1) equalize prediction accuracy for burn and no-burn labels, which also equalizes type I and type II errors or sensitivity and specificity (*balanced accuracy*) and (2) maximize overall model accuracy relative to field-level labels (*max accuracy*).[29] The mean of the trained RF models was then applied to unlabeled pixels aggregated to field-level burn outcomes to generate binary burn estimates for the full data set. When estimating treatment effects, we invert the burning classification so that a no-burn outcome is a one, for consistency with other contract outcomes (a higher value is an environmental improvement).

The RF model is trained on negative labels that are available for the treatment group only (and positive labels for both the treatment and control groups). This has the potential to 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, Appendix Figure A.3 shows that the distributions of the fields classified as a burn or no-burn by the continuous RF output is similar in the treatment and control groups. Formal statistical tests for equal distributions, conditional on classified burning status, confirm no statistical difference in the distributions.

The balanced accuracy model has an overall accuracy of around 78 percent (see Table A.1), the max accuracy model does better (by definition), though only modestly (82 percent). The models make different tradeoffs: the latter is slightly more accurate but has potential to under-count negative labels (no-burn outcomes). Thus, it might understate the rate of non-burning, which should not affect the treatment effect size, but would cause us to understate non-burning in the control group and overstate the proportional impact of the treatment on non-burning. As a conservative approach, we use the balanced accuracy results as our main

[29]Because burning is more common than not burning, the overall accuracy is improved at the expense of accuracy in predicting no-burns. We present robustness checks over a wide range of classification thresholds.

outcome, and also show results using the max accuracy model.

3.5 Outcome and heterogeneity measures

Outcomes Our main outcome of interest is farmer residue burning. We measure it using multiple data sources, as well as ancillary outcomes that are likely to be related to burning. First, we use data on contract compliance to construct two measures: whether a farmer called for monitoring and whether the farmer was found to have not burned when a monitoring visit was made. These outcomes allow us to compare the differential treatment effect of standard PES versus upfront PES. However, lack of these data for control group farmers and for farmers in the treatment group who did not call for monitoring, means we cannot use it to benchmark against the status quo and measure cost effectiveness or impacts relative to counterfactual burning. Second, we use remote sensing measures available for all farmers, which offer predicted not-burning, but are measured with some error. Finally, we rely on endline survey data for measures of residue management practices across treatment and control farmers, which include the main alternatives to burning: balers (ex-situ) and Happy Seeders (in-situ).

Distrust and liquidity constraints Following our pre-analysis plan, we use baseline data to construct a distrust index and a financial constraints index. An important caveat is that neither measure is specific to choices around residue burning. Specifically, since our study population had no experience with PES programs, and over 40% had no experience with CRM equipment, our survey asked about generalized trust and general financial constraints related to agriculture.[30] In the endline, we directly asked treatment group farmers about trust in a PES program, or financial constraints specific to CRM.

We also construct indices of CRM equipment access, which may affect take-up or compliance with PES programs as a whole. We construct three sub-indices to measure different types of access barriers: informational barriers (i.e., awareness of alternatives to burning and knowledge of where to rent them), CRM equipment access barriers (including delays), as well

[30]The two baseline indices have a relatively low correlation (0.12), indicating that there is substantial independent variation across them.

as negative beliefs about the impact of CRM equipment on soil health and agricultural yield. The survey questions used in the construction of these indices are reported in Appendix A.2.

4 Results

We first outline the estimation strategy and show evidence supporting internal validity. We then present treatment effects on farmer behavior (contract outcomes, satellite-imagery based burning outcome, and survey measures on the use of specific burning alternatives). Finally, we provide suggestive evidence on mechanisms.

4.1 Estimation strategy

We estimate the following equation:

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

where y_{ij} denotes an outcome for farmer i in village j, $StandardPES_j$ is a binary variable that takes the value 1 if village j is assigned to the standard PES treatment, $UpfrontPES_j$ takes the value 1 if village j is assigned to the upfront PES treatment, and X_j are strata fixed effects. Following our pre-analysis plan, and to increase statistical power, we pool the treatment variants (different payment levels in $StandardPES_j$ and different proportions paid upfront in $UpfrontPES_j$). Standard errors are clustered at the village level (the level of treatment). β is the effect of being assigned to the standard PES treatment, and γ the effect to of being assigned to the upfront PES treatment (each relative to the control group).

Balance checks and summary statistics Table 1 presents summary statistics and four types of balance tests: for the treatment (pooling all treatment arms) versus control group, for the standard PES (pooling ₹800 and ₹1600 per acre) versus the control group, the upfront PES (pooling 25% upfront and 50% upfront groups) versus the control group, and for the upfront PES versus standard payments PES. We observe slight imbalance in measures of non-agricultural income, land size, and CRM indices, but the p-value of the joint F-test is

0.34. Importantly, self-reported burning in 2018 is balanced in each comparison.

From Table 1 we glean that our respondents have significant farming experience. They are typically small scale farmers producing on about five acres of land, with majority of household income from agriculture and a mean agricultural income of ₹106,800 (median is ₹50,000).[31] At baseline, 68 percent of farmers self-reported burning their fields in the previous year, though the actual value is likely higher. Less than half the sample, 44%, reported having signed a written contract before.

We have no attrition for our main outcomes of PES compliance and remotely-sensed burning. For the endline survey, Appendix Table A.2 shows that a reasonably high response rate for a phone survey (greater than 80%) but with some differential attrition; the treatment group was about 5 percentage points less likely to respond.[32] For endline survey outcomes, we therefore report both the point estimates as well as upper and lower bounds on our estimates following Lee (2009), which estimates bounds on treatment effects by dropping, in turn, the lowest and highest outcomes in the less-attrited group by the fraction of differential attrition (such that the fraction of responses is equal in treatment and control).[33]

4.2 Treatment effects

A. Did farmers take up the PES contract offers?

In Table 2, we start by examining the differences across treatment arms in whether the surveyor was able to locate and offer the farmer the PES contract, as well as whether the farmer was deemed eligible (i.e., he 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 the details of the contracts. The surveyor was able to locate farmers in treatment arms at a similar rate – 87.9% in the upfront PES

[31] This baseline measure of agricultural income helps interpret the magnitude of the contract payments; the maximum payment in the base contract of ₹800 per acre is ₹8,000 per farmer, or about 16% of median agricultural income.

[32] 8.06% of the sample had an invalid number, and 4.84% of the sample could not be reached in any of eight attempts. These account for the bulk for the attrition, with the remainder due to the following: 1.08% of the sample did not pick up the phone, we had the wrong number for 0.12%, 0.59% refused to talk prior to the consent, 1.19% did not consent to the survey, and 0.96% did not complete the survey.

[33] Since the experiment is stratified, we trim observations from the control group within strata. To obtain the Lee bounds, we run treatment regressions in the trimmed samples including strata fixed effects.

treatments versus 88.5% in (column 1). The same holds for whether the farmer was found *and* was eligible for the treatment, 83.3% in upfront treatments and 84.4% in the standard treatments (column 2). Thus, to convert the intent-to-treat estimates below as effects per person offered the PES contract, multiply by a factor of about 1.2.

Next we consider program take-up, which is again zero by construction for control farmers. Take-up (i.e. whether farmer signed the PES contract) was high, with around 72% of farmers in the treatment arms signing the contract. Take-up does not depend on inclusion of upfront payments in the contract. Conditional on being found and being eligible, the probability that a farmer signed on to the PES program is very high (around 87%). This is surprising, but recall that when farmers were offered the contract, the upfront arm was not given the upfront cash immediately; the cash was transferred to their back accounts 2-3 days after the contract offer. Thus, trust barriers might have deterred even those who, in actuality, could have received "free money" from taking up the contract and providing us with their bank account information. The option value associated with the contract is high in both treatments (Oliva et al., 2020), which also supports the conjecture that farmers who refused may have been objecting to sharing bank account information or granting access to their plots for monitoring.[34]

B. Did farmers offered PES contracts reduce their residue burning?

As an initial indication of impacts on residue burning, we analyze the effect of treatment on whether the farmer called for monitoring and whether, in the monitoring visit, they were found in compliance with the contract (no fields were burned). As shown in Table 3, column 1, around 11% of the farmers offered the standard PES contract called for monitoring. The rate is nearly twice that, around 21%, for farmers offered upfront payments. The difference between the two is statistically significant ($p < 0.01$). Compliance with the contract (a binary variable that is 1 if monitoring revealed no sign of burning and 0 if monitoring was not requested or if monitoring indicated burning) shows a similar pattern (column 2), with

[34]Take-up is not correlated with our baseline measure of trust, but this might reflect its deficiencies as a measure. Those who were offered the contract and declined subsequently burned at a higher rate than the control group, according to our remote sensing measure, suggesting that there was selection into take-up based on expected returns.

about 9% of farmers complying with the contract in the standard PES group and about 18% of farmers complying in the upfront PES group (once again, equality between the two groups can be rejected with $p < 0.01$). Thus, despite an equal likelihood of contract take-up in the standard and upfront PES treatments, upfront payments make farmers twice as likely to actually comply with the contract, with a roughly 10 percentage point wedge between the treatments on both outcomes. Appendix Figure A.5 shows results for the four treatment arms. Paying more in the standard PES variants (₹1,600 vs 800) increased the point estimate on compliance by over 50%, though the difference between the two standard PES variants is not distinguishable from zero. Moreover, compliance with the ₹1,600 arm is much lower than with either upfront arm. This result is striking given that the upfront contract only pays ₹800 per acre. Comparing the two upfront arms, it is theoretically ambiguous which should perform better, as increasing the upfront payment meant a lower reward for compliance; we find almost identical effects for the two variants.

Table 3, columns 3 and 4 consider remote-sensing based measure of whether a farmer burned any fields where our farmer-level measure of not burning is defined as 0 if the farmer burned any of his plots.[35] Columns 3 and 4 presents results using the balanced accuracy and max accuracy classifications, respectively. Treatment effects are similar across the two models. Similar to the results for contract compliance, upfront PES treatment perform better. It increases the rate of not-burning by 8-11 percentage points relative to the control group. The standard PES treatment is statistically zero with small and even negative coefficients relative to the control group.[36] This implies that the payments in the standard PES treatment were entirely inframarginal: these farmers would not have burned their fields even in the absence of the program.[37] The main difference across the two remote-sensing models is in the control group mean, which is around 21 percent in the balanced accuracy classification and 11 percent in the max accuracy classification.[38] This variability in the estimated control

[35] About 18% of the sample had at least one plot predicted to be burned and at least one plot predicted not burned. For this reason, we present plot-level treatment effects in Table A.3.

[36] Treatment effects estimated on our subsample for which we have spot check data are similar in magnitude (see Appendix Table A.4), but with considerably lower statistical power and a (mechanically) higher control group mean given that not all burns were detected through a one-time surprise field visit.

[37] Appendix Figure A.5 shows that neither standard PES contract variants increase the no burning outcome, relative to the control group. Consistent with the contract compliance results, the mean in the ₹1,600 group is (insignificantly) higher than the mean in the ₹800 group.

[38] The underlying remote sensing model is the same for the two classifications, as discussed above, but

group mean does not affect interpretation of the upfront PES arm's effectiveness at lowering burning, but does affect whether one should conclude that some farmers left money on the table. With the higher control group mean estimated in the balanced accuracy model, the implied rate of not-burning in the upfront villages is 31%, which means that some farmers in the upfront arm who did not burn also did not call for the conditional payment.[39]

Appendix Figure A.5 presents results separately for the four treatment arms for program compliance and burning. The point estimates for all outcomes other than contract take-up are larger for the upfront PES arms.

Next, we turn to the endline survey to investigate what farmers did instead of burning. In Table 4, analyze treatment effects on the main *ex situ* and *in situ* alternatives to burning: baler and Happy Seeder use. Greater baler use – an increase of 10 percentage points, about 50% relative to the control and standard PES treatment means – can explain all of difference in compliance between the treatment arms.[40] We see no consistent or detectable measurable changes in the use of the Happy Seeder. Consistent with the null effect of standard PES on our remotely-sensed burning measure, we see no difference in CRM usage in the standard PES arm relative to the control group, suggesting no switch in residue management behavior. To account for differential attrition by treatment status in the endline survey (from where we derive these outcomes). Consistent with the point estimates, we only see a statistically significant increase in baler use (between 8.8 and 14.5 percentage points, the lower and upper bound, respectively) for the upfront PES group.

Two important factors cited by farmers as arguments in favor of residue burning were delays between seasons and agricultural yields.[41] Appendix Table A.5 present treatment effects for yields (in log(tonnes per acre)) for rice and the winter crop, wheat, and for sowing

the threshold used to classify the random forest output as burned or not burned is stricter in the balanced accuracy classification, which leads to more no-burn predictions, on average. Appendix Figure A.4 shows the control group mean and estimated treatment effects as the threshold is varied from a lower bound that classifies all true no-burns as no-burns to an upper bound that classifies all true burns as burns. The treatment effects are more sensitive to the choice of threshold than is the control group mean (top panel).

[39] In the endline survey, some farmers reported having lost the number to call for monitoring or not remembering when they were supposed to call.

[40] Baler use in the control group is around 19% at endline, similar to the rate of burning measured by our main remote sensing outcome.

[41] Given the substantial upfront payouts in the upfront PES treatment, these may also have been directly affected by the contracts.

delays.[42] Neither treatment had consistent impacts on these outcomes.

4.3 Why did upfront payments make farmers comply more?

Across our main outcomes, we show consistent effects that upfront PES payments led to a larger reduction in burning among treated farmers. We explore the reasons why providing partial payment upfront might contribute to these outcomes, starting with our main pre-specified channels of distrust and liquidity constraints.

Panel A of Table 6 presents heterogeneous treatment effects by our pre-specified indices, a financial constraints index and a distrust index. We use binary measures for being above median for the constraint. These baseline measures capture generalized distrust and financial constraints, rather than constraints specific to CRM or the program. We do not find any differential impact of the upfront program by either these generalized financial constraints or distrust.[43]

In the endline survey, we surveyed a subset (63% of the intervention sample) of farmers in the standard and upfront arm about financial constraints and distrust specific to CRM decisions and the PES program. To test for trust in the PES program, we create a binary variable that takes the value 1 if farmers answered yes to the question: "When I was deciding how to manage my stubble during Kharif 2019, I was sure that JPAL would return and pay me the amount owed to me if I did not burn.", and 0 otherwise. To test for the importance of cash constraints in CRM decisions, we asked farmers their level of agreement with the statement "When I was deciding how to manage my stubble during Kharif 2019, shortage of cash limited what methods I could choose for stubble management."[44] We then create a binary variable that takes the value 1 if they picked "not at all important" or "not very

[42]Except for 6 farmers, everyone else (99.6% of the sample) grew wheat in the winter season.

[43]Like all heterogeneity on observables, it could either be that this null result implies the mechanisms are not relevant or that our baseline measures or insufficient heterogeneity in our sample to pick up an effect. Other mechanisms may also be relevant, such as reciprocity. We focus our analysis on our pre-analysis plan, but note that reciprocity appears to be an unlikely mechanism given the high cost of contract compliance and the fact that we observe no differential endline survey participation by treatment arm.

[44]The question about trust in conditional payment was asked only to farmers who signed the contract, while the question about the importance of cash shortages was asked to both farmers who did and didnot sign the contract. We keep the sample comparable for this analysis by only considering the sample who signed the contract, but the results on the importance on cash constraints are similar if we include all respondents.

important" and 0 otherwise.[45] Panel B of Table 6 present the results using these two variables as outcomes. Farmers in the upfront arm are nearly 7 percentage points more likely to say that they trusted the conditional payment to be made if they complied relative to farmers in the standard PES arm – given that our compliance difference is about 10 percentage points across the two, this is an economically and statistically significant effect. On the other hand, farmers in the upfront arm are not more likely to report cash shortages being less relevant for CRM decision-making that season relative to those in the standard arm. We interpret these results as providing suggestive evidence that the upfront payments increased trust in the conditional payments materializing with compliance. That said, cash constraints seem to be a large barrier to compliance, even for those in the upfront arm, suggesting that the upfront amount (which could cover less than half the cost of equipment rental) was too low to ease the constraint.

Appendix Table A.6 presents additional pre-specified heterogeneous treatment effects, including other barriers to complying with the PES contract. These include information constraints about alternatives to burning, barriers to accessing CRM equipment, as well as beliefs about the negative impact of non burning alternatives on yields, pest prevalence, or soil heath. We observe no treatment effect heterogeneity on these variables.

5 Program costs and benefits

In Table 5 we evaluate the cost of the contract payments to facilitate cost effectiveness comparisons. Column 1 shows the treatment effects for amount paid at the farmer-level (zero by construction in the control group),[46] and column 2 the treatment effect on total acres not-burned according to the balanced accuracy classification. Note that the averted burning outcome is the product of the binary not-burning measure analyzed earlier and the farmer's paddy acreage. Column 3 presents the cost per acre of averted burning, which is estimated by dividing the estimates in Column 1 by those in Column 2 for each treatment.

[45] The other options were that shortage of cash was somewhat important or extremely important in determining CRM decisions.

[46] This calculation omits the cost of monitoring contract compliance because the cost is sensitive to the scale of the program and the specific protocols around monitoring. We calculate monitoring costs in our program of around ₹300/field or less than ₹100/acre, which is small relative to the size of the PES payments.

Upfront PES pays out more, both because more people comply and because of the upfront payments to farmers who nonetheless burn. Nonetheless, because of the dramatically higher impact on averted acreage of burning, upfront PES is more cost effective than standard PES. The cost is about ₹2000 per acre.

Next, we compare these costs with the benefits of reducing crop burning. The Global Burden of Disease-Major Air Pollution Sources (Global Burden of Disease Working Group, 2018) reported that an estimated 66,000 lives are lost due to crop burning in India per year, due to pollution exposure. Using a Value of Statistical Life (VSL) of $1 million, this implies total damages of $66 billion per year. From a combined paddy acreage of 17.37 million acres in Punjab, Haryana, and Uttar Pradesh, and assuming 50% of paddy is burned, implies damages of $7599.31/acre (₹606,795.29), which is nearly 300 times the per acre cost of reducing burning through PES with upfront payment.

To put this cost per life saved in perspective, we compare it with other pollution abatement opportunities. Coal-fired power plants are a major source of particulate emissions in India, and installing SO_2 scrubbers lowers emissions of fine particulate. The Global Burden of Disease 2018 estimated 84,650 lives lost due to thermal power in India per year. Installing scrubbers avoids 72% of deaths in the first year (Cropper et al., 2019), which would save 60,948 lives. India has 203 GW coal capacity (Ministry of Power, 2022) – on average, this implies that installing scrubbers in a 500 MW plant would avoid about 50 deaths per year, and costs about $1.2 billion for 20 years, or 60 million per year annualized. Assuming no discounting and constant benefits for the lifetime of scrubbers, the cost per life saved is around $400,000. For comparison, the cost per life saved from our most cost effective treatment is $3,617.55.[47] Thus, while several abatement opportunities have benefits that exceed the costs in India, residue burning reduction provides a much lower cost and higher benefit.

[47]Using above assumptions, crop residue burning causes 0.0075 deaths per acre annually. Reducing one acre of burning costs ₹2,034.87/acre, or ₹271,316 per life saved. At 75 ₹per $, this is $3,617.55 per life saved.

6 Conclusion

Identifying low-cost pollution abatement opportunities allows for efficient use of limited budgets earmarked for environmental protection and mitigates the trade-off with economic development. However, even conditional on identifying promising opportunities, market imperfections such as credit constraints or weak institutions that impact trust in the state can impact the efficacy of policies targeting these abatement opportunities.

We show that crop residue burning, which imposes considerable costs on the environment and human well-being, is a solvable problem. Furthermore, program design that accommodates institutional constraints can improve efficacy considerably. Providing some of the contract payment upfront leads to larger reductions in burning than providing all of the payment after participants have undertaken the costly behavior change. In spite of larger "wasted" payments (i.e., to farmers who continue to burn), PES with upfront payments is cost effective and leads to burning reductions that deliver benefits far in excess of their cost.

While scaling up PES contracts for not burning is, in principle feasible, additional barriers remain. First, monitoring costs are substantial and the monitoring protocols that we implemented were not designed for scale. Alternative approaches to large-scale monitoring, such as remote sensing, are likely to introduce additional risk into the contract or be prone to political manipulation. Second, alternatives to burning remain scarce, and if taken to scale, may raise the cost of not burning. For example, if all farmers started hiring balers, baler rental costs would rise. On the other hand, repeated program implementation would create incentive for innovation in better CRM or improved rental market efficiency. Dynamic incentives would also lower the cost of providing upfront payments, which might also become less important as trust in payments improves.

These concerns aside, the large benefits from reducing burning warrant greater policy attention to this problem. PES programs can be implemented by organizations interested in reducing burning but without the jurisdiction to levy fines. Further innovation may reduce ongoing implementation barriers. More broadly, the magnitude of the environmental damages from crop residue burning in India justify greater investment and research to find viable solutions to this problem, whether through PES or other approaches.

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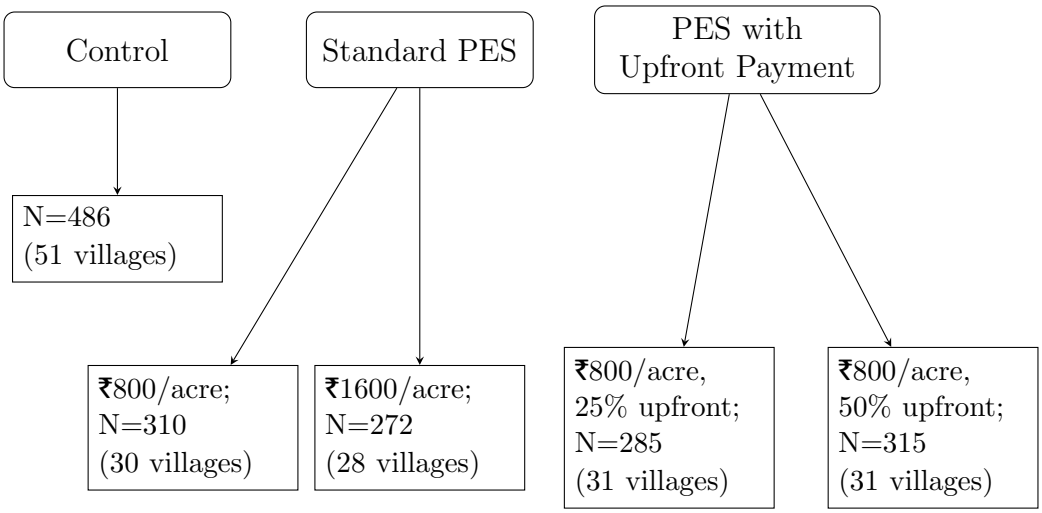
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Figure 1: Design



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

Figure 2: Experimental Timeline

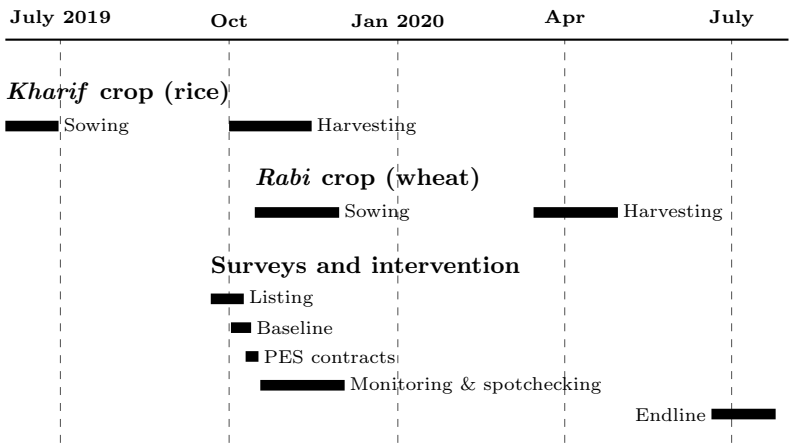


Table 1: Summary Statistics and Balance

	N	Control		Treatment vs Control	Standard vs Control	Upfront vs Control	Upfront vs Standard
		Mean	SD				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Demographics							
Age (years)	1668	48.67	12.73	-0.158	-0.448	0.124	0.610
Total experience in agriculture (years)	1668	28.05	13.14	-0.184	-0.452	0.078	0.522
Highest educational class passed	1658	7.21	4.20	-0.147	-0.200	-0.096	0.114
1(Ever signed a written contract)	1440	0.48	0.50	-0.048	-0.049	-0.048	0.001
Panel B: Income							
Total income	1602	125.69	172.59	-4.655	1.060	-10.190	-10.352
Non-agricultural income	1455	18.08	66.41	-1.393	-2.545	-0.277	3.150
Total agricultural profit	1521	114.18	155.75	-2.759	4.674	-9.905	-14.483
Total agricultural revenue	1603	75.77	157.20	334.013**	463.836	206.532	-249.676
Total area of land in acres (measured)	1668	4.99	2.82	0.327*	0.350*	0.304	-0.049
Paddy production in 1000kg	1513	13.25	9.59	0.684	1.069	0.308	-0.768
Panel C: Heterogeneity variables							
Liquidity constraints index	1668	0.50	0.50	0.011	0.020	0.003	-0.012
Distrust index	1655	0.48	0.50	0.043	0.058	0.029	-0.032
CRM information constraints index	1676	0.44	0.50	0.026	0.062	-0.009	-0.076*
CRM access constraints index	1651	0.45	0.50	0.076**	0.078**	0.073*	-0.009
CRM negative beliefs index	1676	0.50	0.50	0.069**	0.095**	0.043	-0.060*
Panel D: Burning							
1(Burned paddy residue in 2018)	1576	0.68	0.47	0.025	0.044	0.006	-0.037
P-value of joint F Test				0.341	0.3858	0.7032	0.6942

Note: ***(**)(*) indicates significance at the 1%(5%)(10%) level. The table shows the summary statistics for the control group in the baseline. The Treatment column shows the coefficient from regressing the baseline variable on a treatment dummy (taking value 1 if the respondent was in any treatment group). The Standard PES and Upfront payment PES columns are the coefficients from regressing the baseline variable on two treatment dummies (one taking value 1 if the respondent was in a Standard PES treatment group, and one taking value 1 if the respondent was in Upfront payment PES treatment group). Both regressions use the control group as the comparison group, cluster standard errors at the village level and include strata fixed effects. All income variables relate to income derived in the past 12 months and are measured in 1000 Rs. All index variables in Panels C, D, and E are binary. There are 1,668 observations in the baseline; 486 observations for the control group and 1,182 observations for the treatment groups.

Table 2: Program Outcomes

	Farmer Found	Farmer Eligible	Contract Take-Up
	(1)	(2)	(3)
Standard PES	0.885	0.844	0.726
	(0.014)***	(0.019)***	(0.023)***
Upfront PES	0.879	0.833	0.718
	(0.011)***	(0.014)***	(0.022)***
P-value test Standard PES=Upfront PES	0.720	0.627	0.798
Control mean	0.000	0.000	0.000
Standard PES mean	0.887	0.852	0.741
Upfront PES mean	0.880	0.837	0.728
N	1668	1668	1668

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects included. Farmer Found is a dummy variable taking the value 1 if the respondent was available during the intervention. Farmer Eligible is a dummy variable taking the value 1 if the respondent was available during the intervention and had a bank account. Contract Take-Up is a dummy variable taking the value 1 if the respondent signed a contract to participate in the PES program.

Table 3: Contract Compliance and Not Burning

	Called for Monitoring (1)	Complied with Contract (2)	Not Burned (Balanced Accuracy) (3)	Not Burned (Maximum Accuracy) (4)
Standard PES	0.107	0.085	-0.028	0.009
	(0.016)***	(0.015)***	(0.046)	(0.034)
Upfront PES	0.206	0.183	0.110	0.081
	(0.021)***	(0.020)***	(0.047)**	(0.035)**
P-value test Standard PES=Upfront PES	0.000	0.000	0.001	0.040
Control mean	0.000	0.000	0.208	0.105
Standard PES mean	0.108	0.084	0.170	0.102
Upfront PES mean	0.210	0.185	0.313	0.178
N	1668	1668	1664	1664

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects included. Called for Monitoring is a dummy variable taking the value 1 if the respondent called to request monitoring of his plots. Complied with Contract is a dummy variable taking the value 1 if the monitoring lead to the conclusion that the respondent complied with the contract i.e. did not burn his paddy residue. Not Burned takes value 1 if the farmer did not burn any of his plots, and 0 otherwise. Column 3 classifies burning to balance type I and type II errors; column 4 classifies burning to maximize overall model accuracy.

Table 4: Crop Residue Management Methods

	Baler (1)	Seeder (2)
Standard PES	-0.010	-0.020
	(0.037)	(0.023)
Upfront PES	0.096	0.013
	(0.039)**	(0.026)
P-value test Standard PES=Upfront PES	0.014	0.157
Control mean	0.199	0.102
Standard PES mean	0.171	0.087
Upfront PES mean	0.295	0.112
N	1387	1387
Lee Bounds		
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: ***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Baler is a dummy variable taking value 1 if the farmer reported in the endline that he used a baler. Seeder is a dummy variable taking 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 33.

Table 5: Cost Effectiveness

	Amount Paid (1)	Averted Acreage (2)	Cost per Acre (3)
Standard PES	608.026	0.096	6301.244
	(138.176)***	(0.251)	(15882.51)
Upfront PES	1647.519	0.810	2034.872
	(99.998)***	(0.264)***	(609.28)***

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Amount Paid is the payment in Rs the farmer received (it is the total amount for those who were monitored and did comply (i.e. did not burn), it is the upfront amount for any respondents in the treatment groups with upfront component who participated but did not call for monitoring/burned, and it is 0 for respondents in treatment groups without upfront component who did not call for monitoring/burned, for respondents in any treatment groups who did not participate, as well as for respondents in the control group). Acreage Averted is the number of acres not being burned according to the remote sensing data. Cost per Acre is column 1 divided by column 2.

Table 6: Treatment Effects by Liquidity and Distrust

Panel A: Liquidity Constraints and Distrust		
Outcome variable:	Complied with Contract	
Type of constraint:	Liquidity	Distrust
	(1)	(2)
Upfront PES	0.088	0.114
	(0.029)***	(0.030)***
Highly constrained	0.010	0.030
	(0.022)	(0.024)
Upfront PES × Highly constrained	0.018	-0.032
	(0.038)	(0.036)
Standard PES mean	0.084	0.083
Upfront PES mean	0.185	0.185
N	1182	1172
Panel B: Trust in Payment and Importance of Cash Shortage		
Outcome variable:	Trusted Payment	Cash Shortage Not Important
	(1)	(2)
Upfront PES	0.068**	-0.022
	(0.028)	(0.039)
Standard PES mean	0.854	0.315
N	580	584

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. 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 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. 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 is a dummy variable taking the value 1 if the monitoring lead to the conclusion that the respondent complied with the contract i.e. did not burn his paddy residue. The comparison group is the Standard PES group. **Panel B:** Trusted payment takes value 1 if the respondent trusted that the payment by JPAL will be made if they did not burn their paddy stubble , and 0 otherwise. Cash shortage not important takes value 1 if the respondent declared that cash shortage was not an important factor when deciding which crop residue management method to use, and 0 otherwise. These outcome variables are based on self reported data from the endline survey. The control group is excluded from the sample. The comparison group is the Standard PES treatment group. Only those who signed a contract i.e. took up the treatment are included in the sample.

Appendices

A.1 Appendix Tables

Table A.1: Accuracy Statistics, Holdout Sample

Accuracy model:	Balanced Accuracy (1)	Max Accuracy (2)
Mean accuracy	0.78	0.82
False burn	0.07	0.10
False no burn	0.15	0.07
True burn	0.54	0.62
True no burn	0.23	0.19
No burn accuracy	0.78	0.65
Burn accuracy	0.78	0.90

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 fields in each category. N=705.

Table A.2: Attrition from the Endline Survey

	Attrition (1)
Standard PES	0.051
	(0.025)**
Upfront PES	0.044
	(0.025)*
P-value test Standard PES=Upfront payment PES	0.786
Control group mean	0.130
Standard PES group mean	0.187
Upfront payment PES group mean	0.182
N	1668

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. The outcome variable is a dummy that takes the value 1 if the respondent attritted from the endline.

Table A.3: Remote Sensing Based Burning Outcome (Plot Level)

	Not Burned	
	(1)	(2)
Standard PES	-0.021	-0.003
	(0.050)	(0.040)
Upfront PES	0.121	0.100
	(0.050)**	(0.040)**
P-value test Standard PES=Upfront PES	0.002	0.007
Control group mean	0.290	0.164
Standard PES mean	0.251	0.144
Upfront PES mean	0.423	0.280
N	2875	2875

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Plot level regressions are weighted by the inverse of the number of plots the farmer has. Not Burned takes value 1 if the farmer did not burn any of his plots, and 0 otherwise. Column 1 classifies burning to balance type I and type II errors; column 2 classifies burning to maximize overall model accuracy.

Table A.4: Spot Checks Based Burning Outcome

	Not Burned (1)
Standard PES	0.014
	(0.077)
Upfront PES	0.105
	(0.073)
P-value test Standard PES=Upfront PES	0.233
Control mean	0.371
Standard PES mean	0.364
Upfront PES mean	0.456
N	715

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Not Burned takes value 1 if the farmer did not burn any of his plots according to the spot checks, and 0 otherwise.

Table A.5: Yield and Sowing Delay

	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-value test 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			
	Paddy Yield (1)	Wheat Yield (2)	Days (3)
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)

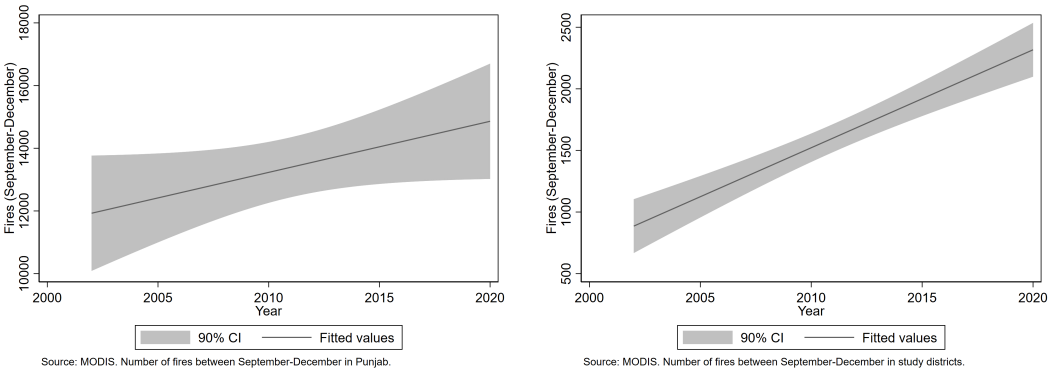
Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Paddy Yield is a variable indicating the amount of paddy produced in Kharif 2019 (log of 1000 kg per acre). Wheat Yield is a variable indicating the amount of wheat produced in Kharif 2019 (log of 1000 kg per acre). Paddy production 2018 is the paddy production in 1000 kg in 2018. Land area is the total area of land in acres the farmer has. Days is a variable indicating 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 33.

Table A.6: Heterogeneity of Treatment Effects on Contract Compliance: 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)**
Standard PES mean	0.084	0.086	0.084
Upfront PES mean	0.185	0.184	0.185
N	1182	1168	1182

Note:***(**)(*) indicates significance at the 1%(5%)(10%) level. Standard errors in parentheses clustered at the village level. Strata fixed effects are included. Type of constraint is the heterogeneity variable which is indicated in the second row of the table: Information Constraints is an index indicating the farmer's lack of knowledge about CRM equipment. Access constraint 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 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 are larger than or equal to the median. The Outcome variable is indicated in the top row: Complied with Contract is a dummy variable taking the value 1 if the monitoring lead to the conclusion that the respondent complied with the contract i.e. did not burn his paddy residue.

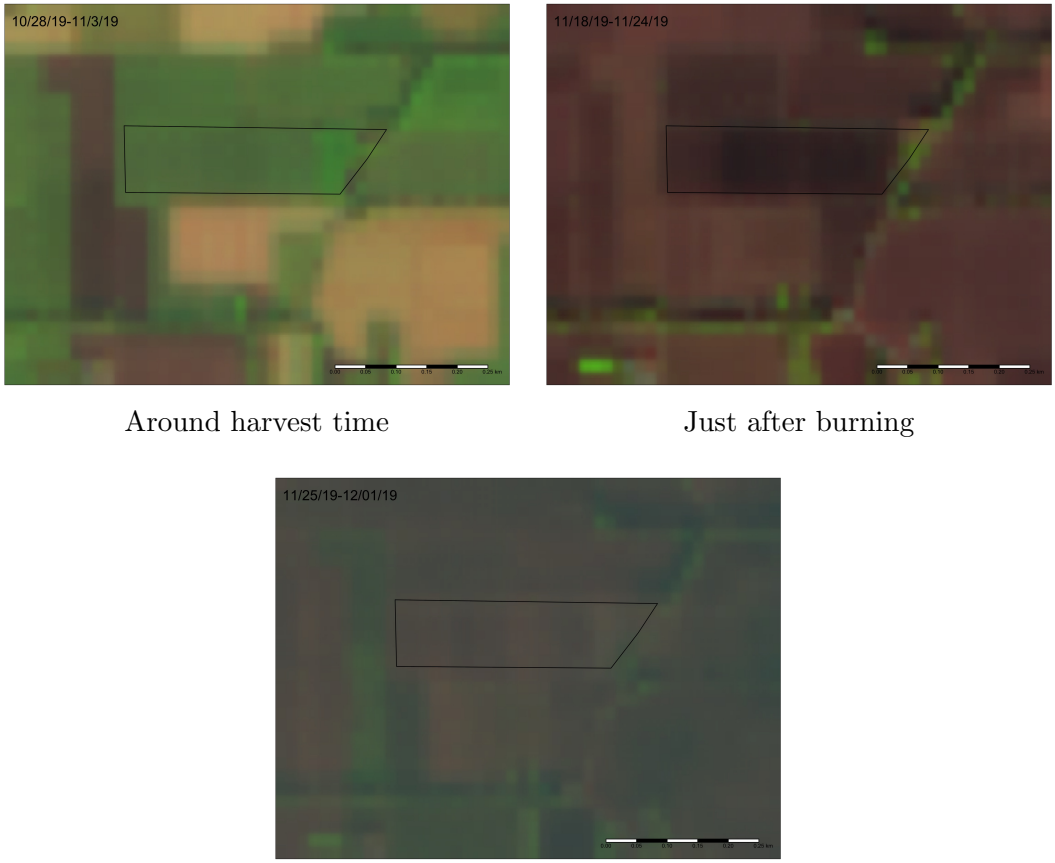
Figure A.1: Fires Over Time: MODIS Satellite Data



Punjab Bathinda and Faridkot

Note: Fire counts by year, based on MODIS imagery. Left panel shows the state of Punjab; right panel shows study districts.

Figure A.2: Signature of Burning in Imagery: Example

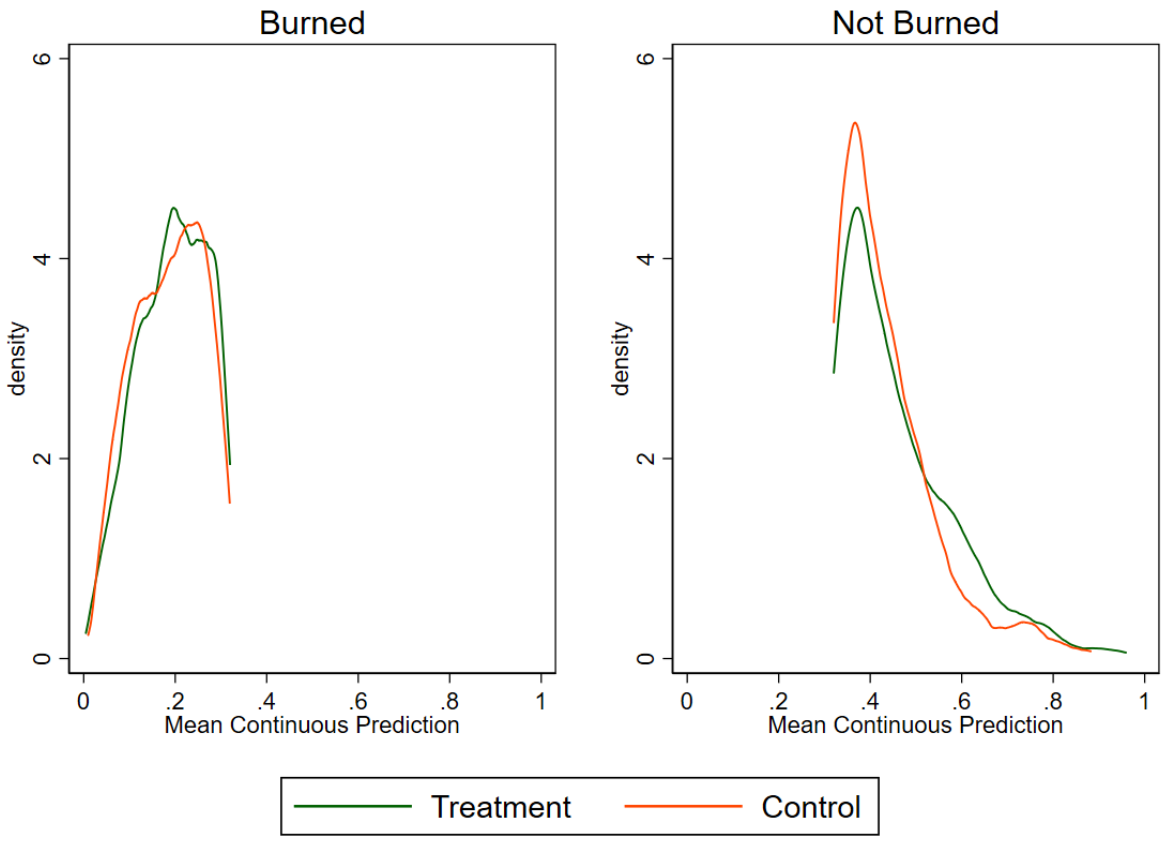


Around harvest time Just after burning

One week after burning

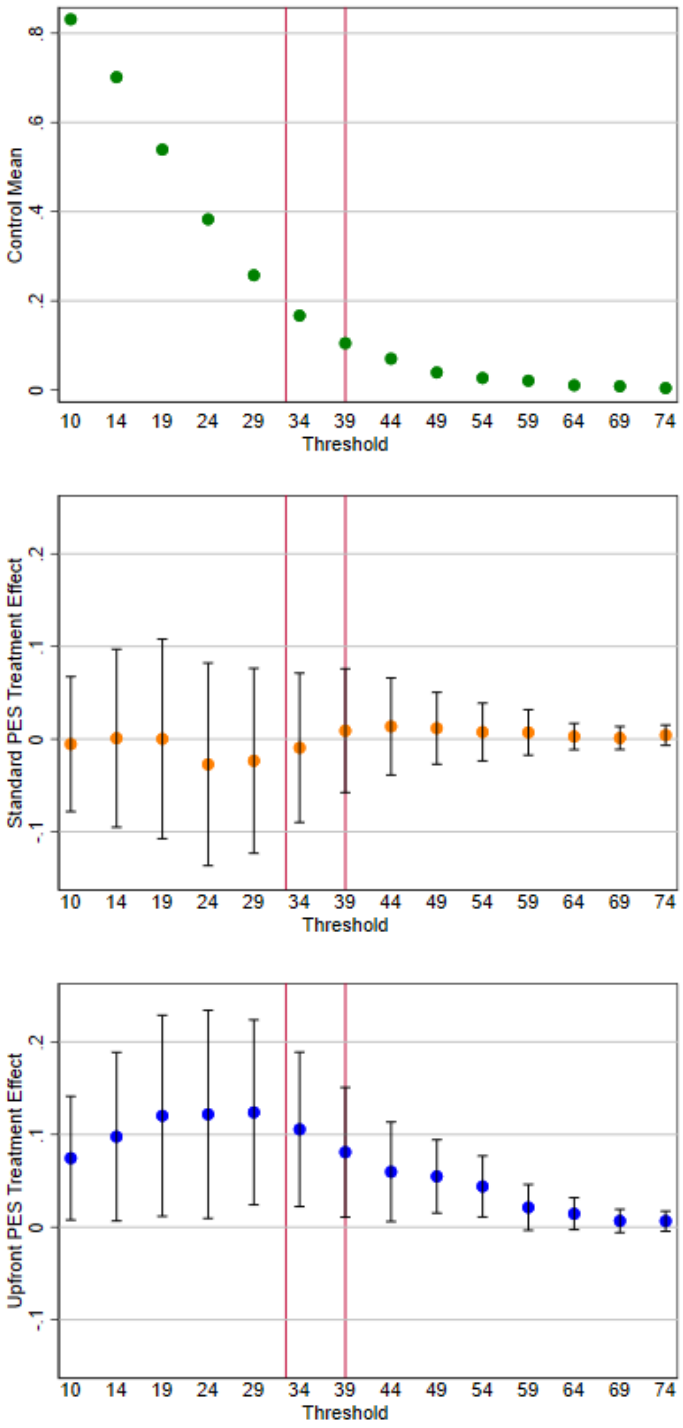
Note: Imagery from Sentinel-2 showing a study field.

Figure A.3: Distribution of Random Forest Predictions by Treatment



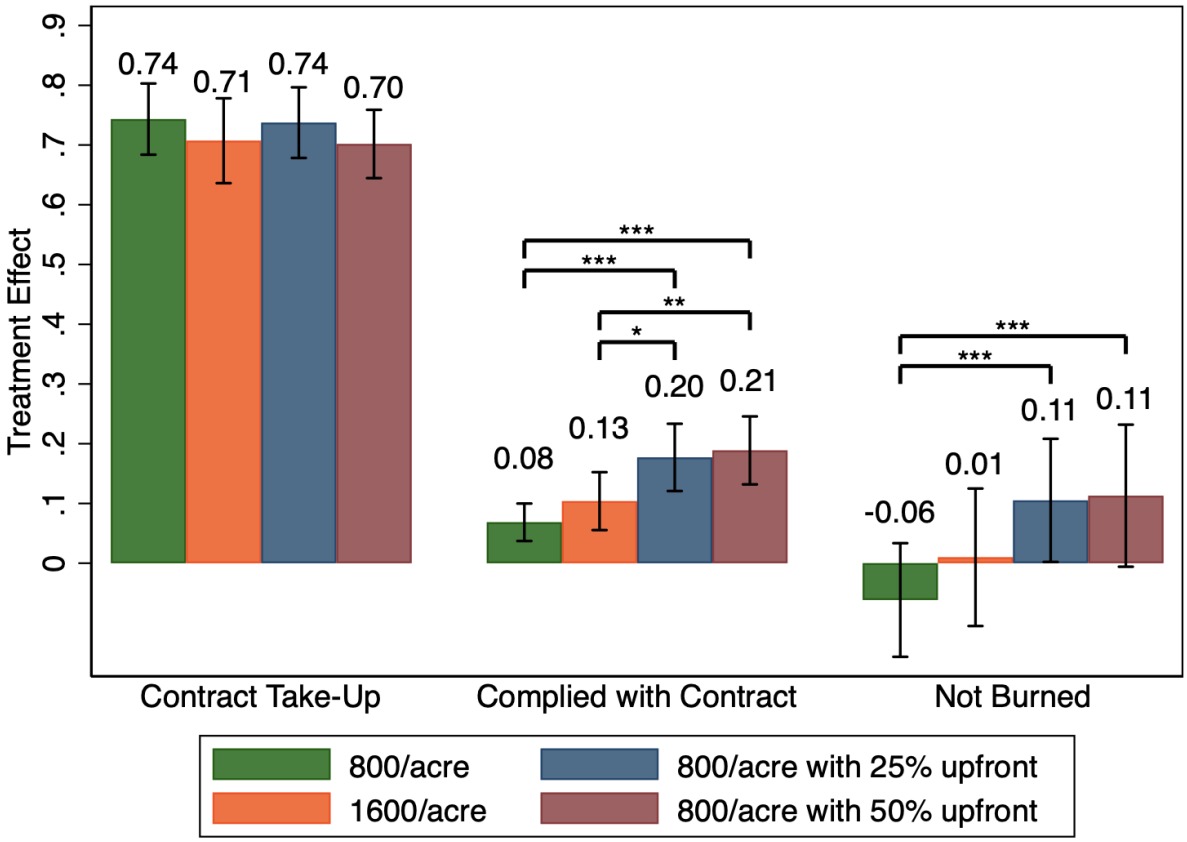
Note: The left panel shows the distribution of the continuous remote sensing measure of not burning for the plots classified as having been burned. The right panel shows the distribution of the same measure for plots classified as not having been burned. The classification uses the balanced accuracy. 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.

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



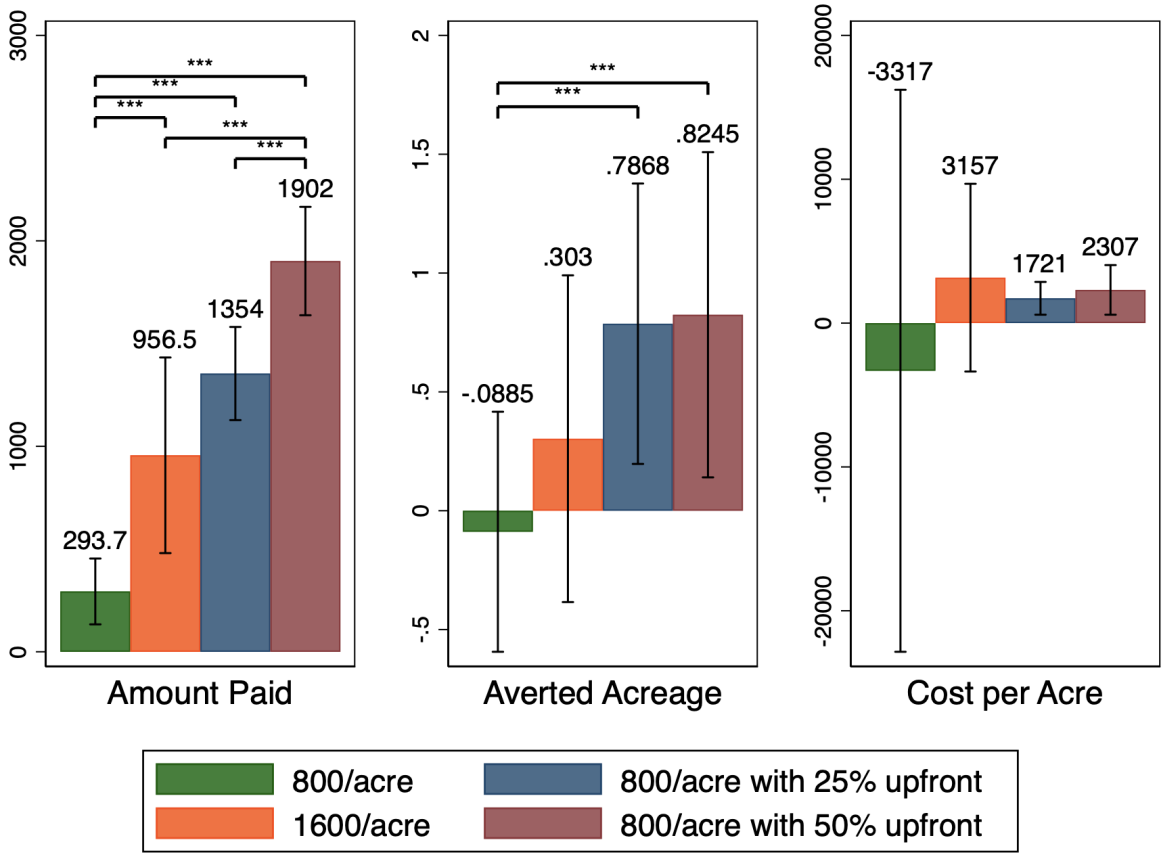
Note: The graphs show the control mean and treatment effects for binary remote sensing measures of not burning based on different classification thresholds. The classification thresholds are indicated on the x-axis. The binary remote sensing measures of not burning take value 1 if the farmer did not burn any of his plots, and 0 otherwise. The first graph shows the mean of the remote sensing measure of not burning in the control group. The second graph shows the treatment effects on not burning in the Standard PES treatment arm. The third graph shows the treatment effects on not burning in the Upfront PES treatment arm. The two red lines in the second and third graph indicate the thresholds used for the remote sensing measures of not burning with balanced accuracy which classifies burning to balance type I and type II errors, and with maximum accuracy which classifies burning to maximize overall model accuracy. The remote sensing measure of not burning with balanced accuracy uses a threshold of 31 and the one with maximum accuracy uses a threshold of 39.

Figure A.5: Treatment Effects on Program Outcomes



Note: Coefficients on top of bars. ***(**)(*) indicates significant difference between coefficients at the 1%(5%)(10%) level. Contract Take-Up is a dummy variable taking the value 1 if the respondent signed a contract to participate in the PES program. Complied with Contract is a dummy variable taking the value 1 if the monitoring lead to the conclusion that the respondent complied with the contract i.e. did not burn his paddy residue. Not Burned takes value 1 if the farmer did not burn any of his plots, and 0 otherwise, using the balanced accuracy which classifies burning to balance type I and type II errors. 800/acre is the Standard PES group receiving 800 Rs. per acre conditional on not burning. 1600/acre is the Standard PES group receiving 1600 Rs. per acre conditional on not burning. 800/acre with 25% upfront is the Upfront PES group receiving 800 Rs. per acre of which they receive 25% unconditionally upfront and 75% conditional on not burning. 800/acre with 50% upfront is the Upfront PES group receiving 800 Rs. per acre of which they receive 50% unconditionally upfront and 50% conditional on not burning.

Figure A.6: Cost Effectiveness



Note: Coefficients on top of bars. ***(**)(*) indicates significant difference between coefficients at the 1%(5%)(10%) level. Amount Paid is the payment in Rs the farmer received (it is the total amount for those who were monitored and did comply (i.e. did not burn), it is the upfront amount for any respondents in the treatment groups with upfront component who participated but did not call for monitoring/burned, and it is 0 for respondents in treatment groups without upfront component who did not call for monitoring/burned, for respondents in any treatment groups who did not participate, as well as for respondents in the control group). Acreage Averted is the number of acres not being burned according to the remote sensing data. Cost per Acre is column 1 divided by column 2. 800/acre is the Standard PES group receiving 800 Rs. per acre conditional on not burning. 1600/acre is the Standard PES group receiving 1600 Rs. per acre conditional on not burning. 800/acre with 25% upfront is the Upfront PES group receiving 800 Rs. per acre of which they receive 25% unconditionally upfront and 75% conditional on not burning. 800/acre with 50% upfront is the Upfront PES group receiving 800 Rs. per acre of which they receive 50% unconditionally upfront and 50% conditional on not burning.

A.2 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 co-operative 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?

Appendix B: 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 burnt. 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 Appendix C: Sample Contract

${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