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

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We test whether payments for ecosystem services (PES) can curb the highly polluting practice of crop residue burning in India. Standard PES contracts pay participants after verification that they met a proenvironment condition (clearing fields without burning). We randomize paying a portion of the money up front and unconditionally to address liquidity constraints and farmer distrust, which may undermine the standard contract's effectiveness. Incorporating partial up-front payment into the contract increases compliance by 10 percentage points, which is corroborated by satellite-based burning measurements. The cost per life saved is $3,600–$5,400. The standard PES contract has no effect on burning. (*JEL* D86, O13, Q12, Q15, Q18, Q53, Q58)

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

Crop residue burning is a classic example of an environmental externality, and the Indian government has responded with a command-and-control approach:

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

since 2015, burning residue has been banned and punishable by fines. However, the externality's interjurisdictional nature and a powerful farmer lobby have undermined political incentives to enforce the ban (Dipoppa and Gulzar 2022). The government also introduced subsidies for farm equipment that removes residue without burning. However, subsidy levels are insufficient to cover the full cost of equipment use and are restricted to certain equipment. With the existing policy mix, crop residue burning remains widespread (Aryal et al. 2023).

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

Contextual and institutional features common in lower-income countries motivate PES but can also restrict its efficacy and that of conditional cash transfers more generally. Before receiving payment, PES participants must undertake the costly action required under the contract. They might not comply if they doubt the payment will be made or if they lack the cash needed to change behavior (e.g., to rent farm equipment to avoid burning). PES contracts that offer partial up-front payment may ease these constraints. An up-front payment sends a costly signal, increasing trust that the conditional payment will occur. It also provides liquidity to pay for the costs to comply.

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

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

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

that appropriately designed incentive contracts, particularly those with an up-front payment component, can help policymakers make headway on this critical but difficult problem.

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

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

I. Background and Study Design

A. *Crop Residue Burning and Policy Responses*

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

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

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

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

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

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

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

B. *PES Contracts and Randomization Design*

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

Based on discussions with the Punjab government about a scalable payment level, we set our base standard PES contract, which pays out only once the absence of burning is verified, at ₹800 per acre. To assess the importance of payment amounts, we introduced another standard PES contract that pays twice as much, ₹1,600 per acre.[7]

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

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

Our second treatment arm addressed trust and liquidity concerns by paying a portion up front and the rest contingent on verified nonburning. To match our base contract, the sum of the (potential) up-front and ex post payments was set at ₹800. The only difference between the two subtreatments was whether 25 percent or 50 percent was paid up front. Supplemental Appendix Figure A1 summarizes the experimental design, which also includes a status quo control group (51 villages).[8] Supplemental Appendix Figure A2 depicts the timeline for data collection and agricultural activities.

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

C. *Sampling and Baseline Survey*

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

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

In over 90 percent of households, the person surveyed made household agricultural decisions. We collected data on demographics, agricultural production, income and credit constraints, trust in organizations, and barriers to CRM use. Over half of study farmers' household income is from agriculture, with a control group mean agricultural profit of ₹114,000 (median: ₹58,000). Roughly half (48 percent) had

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

[9] Supplemental Appendix Table A1 compares eligible farmers to all farmers, based on a census of four study villages.

ever signed a written contract. As per our preanalysis plan, we construct distrust and financial constraints indices from baseline data. We also construct CRM equipment access indices; access might affect PES compliance but to a similar degree in standard and up-front PES (see Supplemental Appendix D for survey questions used for indices). In the survey, farmers listed all paddy plots and accompanied the enumerator to collect geocoded plot perimeter measurements. Plot perimeters formed the basis for monitoring farmers' contract compliance and for linking satellite imagery to plots.[10]

D. *Contract Implementation*

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

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

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

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

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

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

E. *Outcome Data*

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

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

We train a random forest (RF) model using validated (ground) data and high-resolution satellite imagery for a subset of plots. Our validated data comprises monitoring data for treatment farmers and data from spot checks conducted on one randomly selected plot for 50 percent of farmers per village in November 2019. Spot checks and monitoring visits followed similar protocols; however, unlike monitoring visits, spot checks could not be synchronized with the farmer's residue management timing.[14] The satellite imagery comes from two complementary sources, PlanetScope and Sentinel-2.[15] The higher frequency PlanetScope data (roughly every two to three days) is less likely to miss burning events. This is important because burned plots become observationally similar to unburned plots once the soil is tilled for rabi planting (see Supplemental Appendix Figure A3 for an example). Sentinel-2 data (every seven to ten days) also covers the mid-infrared range, which helps distinguish burned and unburned plots.

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

The RF model outputs a pixel-level continuous score ranging from zero to one, representing the proportion of decision trees per pixel classified as burned by the model. To aggregate pixel-level scores to a plot-level burning outcome, we average the score across pixels in a plot (omitting perimeter pixels) and select the plot-level classification threshold (above which a plot in the training data is classified as burned) that maximizes overall prediction accuracy relative to the plot-level label. To avoid model overfitting, we hold out each (multipixel) plot from the training set and obtain a prediction for the held-out pixels (leave-one-out cross-validation). The trained models are averaged and applied to both labeled and unlabeled plots. Specifically, we use the trained pixel-level RF model to predict pixel-level outcomes, then apply the classification threshold from the training set to aggregate up to the plot level. This procedure

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

[15] PlanetScope has 3-meter resolution and Sentinel-2, 20-meter. Other commonly used sensors (MODIS and VIIRS) have lower resolution, 375 meters to 1 kilometer, which is too coarse for the small plots in our study.

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

produces our primary "maximum accuracy" outcome measure, which has 82 percent accuracy. Since the maximum accuracy classification predicts burn outcomes more accurately than no-burn outcomes, we provide a robustness check using an alternative classification threshold that balances the accuracy of predicting burning and nonburning in the training data. This "balanced accuracy" outcome measure has 78 percent accuracy. Supplemental Appendix E and Walker et al. (2022) provide additional detail on the data, data processing, and machine learning model.

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

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

F. *Experimental Validity*

We report four balance tests: pooled treatment arms versus control group, standard PES versus control group, up-front PES versus control group, and up-front PES versus standard PES (see Supplemental Appendix Table A2). The p-value of the joint F-test is 0.48 between treatment and control and 0.81 between standard and up-front PES. Self-reported burning in 2018 is balanced in each comparison. We observe slight imbalance for land size and CRM indices in some tests.

Our PES compliance and remotely sensed burning outcomes have no attrition. In the endline survey, which had 17 percent attrition overall, the treatment group response rate was 5 pp lower than the control group, while the standard and up-front PES response rates were similar (see Supplemental Appendix Table A3). Supplemental Appendix Table A4 shows that this endline attrition does not vary systematically with baseline characteristics. For analyses using endline survey data, we show robustness to using Lee bounds (Lee 2009).

II. Results

We estimate the following equation:

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

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

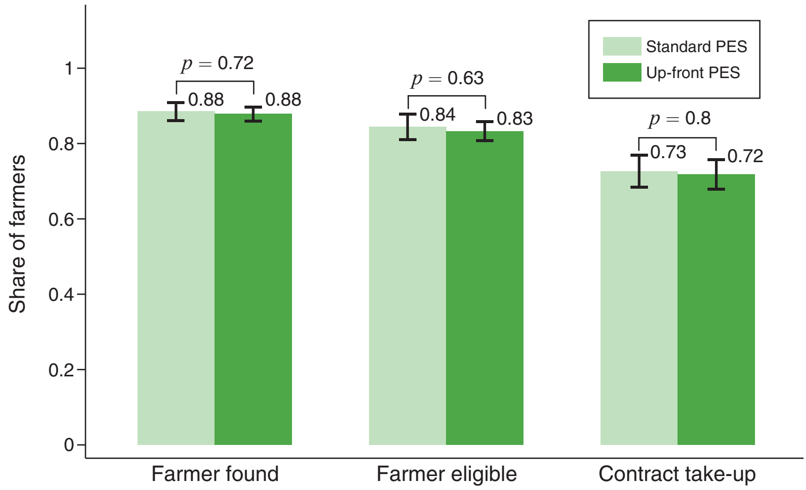

Figure 1. Contract Eligibility and Take-Up

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

A. *Did Farmers Take Up PES Contract Offers?*

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

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

B. *Did PES Treatment Farmers Reduce Crop Residue Burning?*

Table 1, column 1, examines treatment impacts on contract compliance—that is, if the farmer requested monitoring and no plots were recorded as burned during the

[17] Supplemental Appendix Table A6 shows similar take-up rates across all subtreatments.

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

		Unburned		CRM techniques	
	Complied with contract (1)	Max. accuracy (2)	Balanced accuracy (3)	Baler (4)	Seeder (5)
Standard PES	0.085	0.020	0.008	−0.010	−0.020
	(0.015)	(0.030)	(0.042)	(0.037)	(0.023)
Up-front PES	0.183	0.077	0.115	0.096	0.013
	(0.020)	(0.032)	(0.042)	(0.039)	(0.026)
p-value: standard PES = up-front PES	0.000	0.071	0.008	0.014	0.157
Control mean	0.000	0.091	0.202	0.199	0.102
Standard PES mean	0.084	0.098	0.198	0.171	0.087
Up-front PES mean	0.185	0.161	0.313	0.295	0.112
Observations	1,668	1,664	1,664	1,387	1,387

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

monitoring visit(s). In the standard PES group, 8.5 percent of farmers complied. Compliance in the up-front arm is 10 pp higher, at 18 percent. Equality between the two groups can be rejected with $p < 0.01$.[18] Thus, up-front payments make farmers twice as likely to comply with the contract.

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

Unlike the estimate for up-front PES, the effect of standard PES relative to the control group is indistinguishable from zero. Thus, standard PES payments were entirely inframarginal: farmers who complied with the standard PES contract would not have burned their plots even in the absence of the program. The p-value for the comparison of the effect on burning for up-front versus standard PES is 0.07. In column 3, we report results using the alternative balanced accuracy measure and see that up-front PES reduces burning by 11.5 pp relative to the control group and 9.8 pp relative to standard PES (p-value < 0.01).

While the effect sizes for the two remote sensing measures—based on different classification thresholds—are broadly similar (7.7 and 11.5 pp for up-front PES relative to control), Supplemental Appendix Figure A4 further explores sensitivity of the effect sizes to the threshold for classifying burning. As the threshold increases, pixels and plots are more likely to be relabeled as burned, so the control mean for

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

being unburned decreases, and this mechanically decreases the estimated treatment effects. For up-front PES, the treatment effect is always statistically significantly positive except at the most extreme threshold. Standard PES never has a statistically significant effect. Supplemental Appendix Table A5 shows additional robustness checks. First, we report plot-level analysis; 18 percent of farmers had at least one plot predicted to be burned and also at least one plot predicted to be unburned. Plot-level treatment effects are of similar magnitude to our main farmer-level result. Second, treatment effects estimated on spot check data are also similar in magnitude but with considerably lower statistical power and an unburned rate in the control group that is mechanically higher because the one-time plot visit missed some burns.

Though we lack statistical power to test for arm-by-arm differences, we describe the effects of each of the four subtreatments briefly (see Supplemental Appendix Table A6). Paying more in the standard PES contract (₹1,600 versus ₹800) results in statistically insignificant increases in compliance and nonburning. Compliance is lower in the ₹1,600 arm than in either up-front PES arm. This is striking given that the up-front contract only pays ₹800 per acre. It is theoretically ambiguous which of the two up-front arms (25 percent up front versus 50 percent up front) should perform better; increasing the fraction paid up front meant a lower reward for compliance. We find similar effects for the two variants, with slightly larger but statistically indistinguishable impacts when 50 percent is paid up front.

In columns 4 and 5 of Table 1, we report treatment effects on the main ex situ and in situ alternatives to burning: self-reported baler and Happy Seeder use. Increased baler usage—by 10 pp—can explain all of the reduced burning achieved through up-front PES; every farmer who switched away from burning due to up-front PES seems to have switched to baling their straw. (The lower and upper Lee bound point estimates are 8.8 and 14.5 pp; see Supplemental Appendix Table A7.) There are no detectable changes in Happy Seeder use in the up-front arm. Consistent with the null effect of standard PES on our remote sensing burning measures, we see no difference in baler or Happy Seeder use in the standard PES arm relative to the control group.[19]

C. *Why Did Up-Front PES Increase Compliance?*

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

[19] Besides lower costs, farmers cite less delay in sowing the rabi crop and higher agricultural yields as benefits of burning. We test for these effects in Supplemental Appendix Table A8. The average effects are statistically insignificant, but the confidence intervals and Lee bounds are wide.

[20] Supplemental Appendix Table A10 presents additional prespecified heterogeneous treatment effects that pertain to the overall effect of PES. Farmers with greater information constraints and more negative beliefs about burning alternatives are less likely to comply with PES, pooling the treatment arms. Supplemental Appendix Table A9 also tests whether program take-up is differential by five prespecified indices (liquidity, distrust, information about CRM alternatives, CRM access constraints, and negative beliefs about burning alternatives).

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

Table 2—Liquidity and Distrust as Moderators of Treatment Effects

Outcome variable	Complied with contract		Unburned (maximum accuracy)	
Type of constraint	Distrust (1)	Liquidity (2)	Distrust (3)	Liquidity (4)
Panel A. Liquidity constraints and distrust				
Up-front PES	0.114	0.088	0.054	0.051
	(0.030)	(0.029)	(0.029)	(0.029)
Highly constrained	0.030	0.010	0.003	0.014
	(0.024)	(0.022)	(0.025)	(0.030)
Up-front PES × Highly constrained	−0.032	0.018	−0.025	−0.022
	(0.036)	(0.038)	(0.039)	(0.042)
Standard PES mean	0.083	0.084	0.104	0.105
Up-front PES mean	0.185	0.185	0.143	0.142
Observations	1,172	1,182	1,168	1,178
	Trusted payment (1)	Cash shortage not important (2)		
Panel B. Trust in payment and importance of cash shortage				
Up-front PES	0.068	0.038		
	(0.028)	(0.043)		
Standard PES mean	0.854	0.441		
Observations	580	584		

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

In the endline survey, we asked a subset (63 percent) of farmers in both treatment arms about trust in the PES program and financial constraints influencing their CRM decisions.[22] Farmers in the up-front arm were 7 pp more likely than farmers in the standard PES arm to say they trusted that the conditional payment would be made if they complied (see Table 2).[23] In contrast, farmers in the up-front and standard PES arms did not differ in how important they said cash shortages were in their CRM decision-making. This does not necessarily imply that up-front payments are

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

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

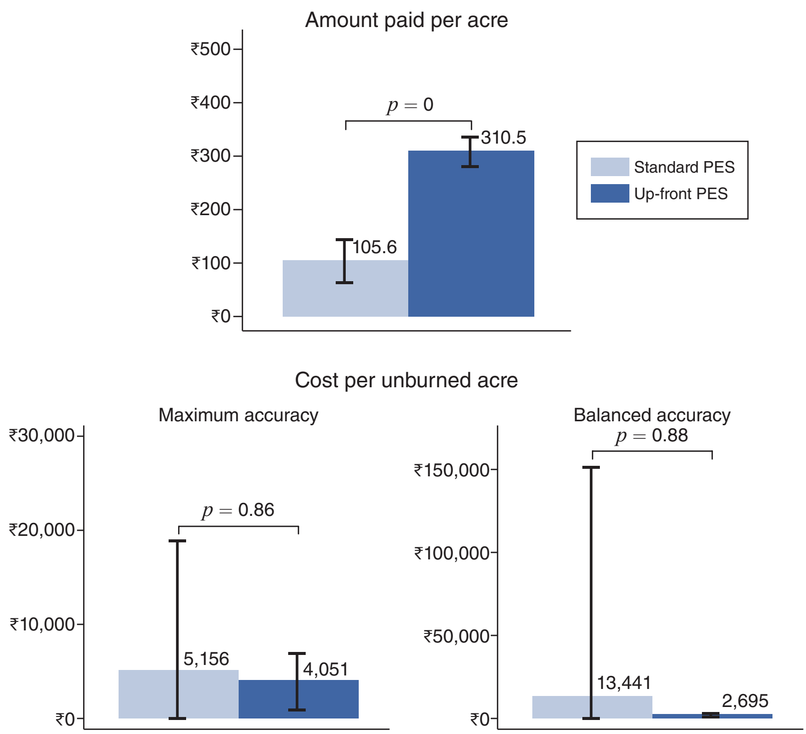

Figure 2. Cost-Effectiveness

Notes: "Amount paid per acre" is the per acre payment the farmer received. This includes the amount paid up front for those in the up-front PES treatment, plus the amount paid conditional on compliance for those in the up-front and standard PES treatments. Treatment effects are estimated using equation (1), which includes strata fixed effects and clusters standard errors at the village level. "Cost per unburned acre" is the "Amount paid per acre" divided by "Unburned" (Table 1), with standard errors calculated using the delta method.

unimportant for easing liquidity constraints and enabling CRM equipment use, as the up-front amount (which could cover less than half the cost of baler rental) may have been too low to meaningfully ease this constraint for most farmers.

III. Program Costs and Benefits

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

To assess cost-effectiveness, we estimate the cost per additional unburned acre by dividing costs per acre cultivated from the top panel of Figure 2 by the treatment effect on the remote sensing outcome measure reported in Table 1.[24] The effect

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

of standard PES on nonburning is small and statistically imprecise, which makes cost-effectiveness comparisons across arms highly imprecise. Specifically, using our main remote sensing model (maximum accuracy), up-front PES costs ₹4,050 ($51) per unburned acre, compared to ₹5,157 ($64) for standard PES (bottom-left panel of Figure 2). With the alternative balanced accuracy model, up-front PES costs ₹2,695 per unburned acre, compared to ₹13,441 for standard PES (bottom-right panel). Even with this stark difference in point estimates, the lack of precision when comparing the estimates makes it hard to draw policy conclusions. Accordingly, we conduct the cost-benefit calculation using results from the up-front arm only.[25]

We benchmark these costs against a rough estimate of the averted-mortality benefits of reducing crop burning. Lan et al. (2022) combine satellite data on fire intensity with air transport models to estimate 86,000 premature deaths from crop residue burning in India in 2018, 43 percent of which can be attributed to kharif burning in Punjab.[26] Estimates of the value of a statistical life for India range from around $688,000 (Majumder and Madheswaran 2018) to $5.6 million (Madheswaran 2007). Using the lower bound of this range as a conservative estimate, this implies over $25 billion in annual damages from burning in Punjab. Kumar et al. (2019) estimate that around 4 million acres of Punjab's (nonbasmati) paddy was burned in the kharif season of 2018. Combining these assumptions, the lower bound of mortality damages of burning are about $6,400 per acre (₹513,000), which is 125 to 190 times the per acre cost of reducing burning through PES with up-front payment. Put differently, the cost of up-front PES was $3,600 to $5,400 per life saved.

IV. Conclusion

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

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

[25] Inputs to the cost-benefit calculations are provided in Supplemental Appendix F.

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

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

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

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

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