Mechanizing Agriculture: Impacts on Labor and Productivity

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Abstract

The mechanization of production has become a primary feature of modern agriculture and is central to agricultural labor productivity. This paper constructs the first available estimates of the returns to mechanization and its impact on labor using a randomized controlled experiment. Treatment farmers were given subsidy vouchers to access agricultural equipment from a nearby custom hiring center (CHC). In addition to these vouchers, a subset of treatment farmers were given cash transfers. The voucher treatment increases overall mechanization hours, with an intent to treatment effect size of about 0.1 standard deviations (a treatment on the treated effect size of 0.3 standard deviations). We find no evidence of positive returns to mechanization on average, but find larger returns to mechanization for larger land-holdings. Family labor supply, which we document to be mostly occupied in supervision activities, decreases in response to the subsidy in capital. At the same time, farmers hire more workers. We interpret the decline in supervision labor and the persistent effect of mechanization on hired labor in other farming processes as evidence of output standardization, which is beneficial in the presence of contracting frictions.

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1 Introduction

The mechanization of production has become a primary feature of modern agriculture (Manuelli and Seshadri, 2014) and is central to agricultural labor productivity (Caunedo and Keller, 2020). However, modern agricultural equipment is more likely to be profitable on larger farms (Foster and Rosenzweig, 2017), and most of the agriculture production in poor economies is done by smallholder farmers (Adamopoulos and Restuccia, 2014). Evidence on the path to mechanization for now rich economies suggests that equipment rental markets were a stepping stone to that process (Binswanger, 1986). To the extent that these rental markets overcome indivisibilities in the purchase of equipment that prevent the adoption of mechanized practices by smallholder farmers, they are of first order relevance to the transformation of rural economies. Yet, adoption of mechanized practices is not always efficient, even when rental options are available, because mechanization requires minimum operation scales. When does mechanization generates productivity improvements?

The literature has emphasized how the adoption of mechanization in agricultural production has first order effects on labor use (Binswanger, 1986). Mechanization may be labor substituting or crowd in labor to the farm by standardizing certain outputs. Less attention has been paid to the differential role that family and hired labor have in the presence of contracting frictions. The lack of observability of intermediate agricultural production generates differences between the tasks performed and the productivity of family vs. hired labor (Bharadwaj, 2015). Therefore, it is possible that mechanization has disparate effects on these types of labor, both through task replacement, and through labor productivity.

This paper constructs the first available estimates of the returns to mechanization and its impact on labor using a randomized controlled experiment. In partnership with one of the biggest providers of rental agricultural equipment in India, we conducted a large randomized control trial to increase access to rental markets for mechanization. One challenge of identifying the effect of mechanization on productivity is the endogeneity between input choices

and farm size (Benjamin, 1992; LaFave and Thomas, 2016; Bardhan, 1973; Deolalikar and Vijverberg, 1983; Jacoby, 1993), which makes observational data inherently problematic to assessing returns. By running a randomized controlled trial that exogenously changes the cost of an input that benefits from scale, i.e. mechanization, we circumvent this problem. The experiment covered 7,100 farmers across nearly 200 villages in the state of Karnataka. Farmers were given subsidy vouchers to access agricultural equipment such as tractors, rotavators, and cultivators from a nearby custom hiring center (CHC). In addition to these vouchers, a subset of treatment farmers were given cash transfers worth half of the voucher amount. Vouchers were valid for redemption throughout the agricultural season, allowing farmers to optimally allocate the use of equipment across agricultural processes.

We collect detailed data on inputs and output by production process, e.g. plant preparation, harvesting, etc., to identify the effects of mechanization on labor use, input choices, and agricultural productivity. We combine this information with administrative data from our implementation partner, which contains the universe of all transactions across all their CHCs, hours of service, type of equipment, area serviced, prices, and repeated interactions. Our data allow us to test whether vouchers increased mechanization for treatment farmers, or treated farmers substituted into subsidized mechanization rentals, and away from unsubsidized rental providers in their own villages. We also track movements in input prices, including labor and rental services. Importantly, cash transfers are key to disentangle income effects from mechanization returns in production, as well as potential credit constraints in renting from other unsubsidized providers.

During the intervention, we find that treatment farmers are 30 percentage points more likely than control farmers to rent agricultural equipment from the CHCs. These effects are heterogeneous by operational land-holdings, with larger farmers being more likely to take up the mechanization rental. Once the vouchers expire, the treatment effects on CHC rental use fall to less than one percentage point, indicating that the price subsidies are responsi-

ble for higher take-up. Importantly, the voucher treatment increases overall mechanization hours, with an intent to treatment effect size of about 0.1 standard deviations (a treatment on the treated effect size of 0.3 standard deviations). Hence, the treatment did not only substitute unsubsidized rental hours from non-CHC sources for subsidized CHC rental hours, but increased mechanization use on average. Interestingly, we find no differential response of mechanization hours per acre between large and small land-holdings. Finally, both take-up and overall mechanization hours are not affected by cash transfers. With these results at hand, we characterize the impact of the induced mechanization on labor, other inputs of production and productivity. Our results indicate that family labor supply, which we document to be mostly occupied in supervision activities, decreases in response to the subsidy in capital. At the same time, farmers hire more workers for production both during land preparation, when mechanization use increases; and harvesting, when treatment has no effect on mechanization. We interpret the decline in supervision labor and the persistent effect of mechanization on hired labor in other farming processes as evidence of output standardization, which is beneficial in the presence of contracting frictions.

A major hypothesis for the differences in agricultural productivity across countries is the incomplete diffusion of technologies that are available in the developed world (Caselli and Wilson, 2004; Foster and Rosenzweig, 2010a). This "underutilization" of a technology should be reflected in higher returns, i.e. unrealized gains. In our experiment, we find no evidence of positive returns to mechanization on average, either measured by profitability or revenue per acre. Because we also find no evidence of price shifts, this finding implies nil returns in output per acre to mechanization on average for smallholder farmers (the average operating landholdings in our sample is 2.5 acres). At the same time, we find larger returns to mechanization for larger land-holdings, with an additional acre increasing returns by about 27 percentage points. This heterogeneity is consistent with the presence of returns to scale and highlights the importance of evaluating returns differently across farmers of disparate

land-holdings.

How is it possible that average productivity does not increase for adopters while average mechanization hours and labor respond to the subsidy and input prices do not change? To interpret the experimental results we construct a structural model where farming tasks can be produced by machines or supervised labor, and where unsupervised labor is complementary to those tasks. The effects of treatment on take up, mechanization hours and labor allocation are readily rationalized by this simple framework. In the model, a subsidy on capital affects productivity per farm through three channels: a capital intensification channel, a task intensification channel and a comparative-advantage effect. The first channel works as in the neoclassical framework: higher capital intensity lowers the marginal product of capital and induces lower average productivity. The second channel works as in models of task specialization where a lower cost of capital implies that more tasks are executed by capital, increasing its factor share. The third channel also works through the change in tasks allocations, but this time through improvements in productivity due to comparative advantage of a factor over other, e.g. capital over supervised labor. If the capital intensification channel dominates the last two, average productivity may stay the same or even decline in response to cheaper mechanization.[1]

This paper is related to three main literatures. First, our paper contributes to the literature estimating returns to capital, broadly defined. Udry and Anagol (2006) estimate the internal rate of return to investment in approximately 1600 plots in Ghana, and Karlan et al. (2014) show that insurance is important to spurring investment in addition to easing liquidity constraints. De Mel et al. (2008) provide capital grants for microenterprises in Sri Lanka, and find high returns to capital for microenterprises. However, when technology is embodied in large indivisible stocks, capital ownership may not optimal for small farmers or micro-enterprises. We subsidize access to mechanization rentals instead of equipment

[1]Our data collection is rich enough to, in conjunction with the predictions of the model, allow us to estimate the magnitude of these channels. Subsequent versions of the paper will include these estimates.

purchases, facilitating the use of large, expensive equipment.

Second, to our knowledge, this paper is the first experimental evidence of the impact of mechanization on the labor market, and how mechanization interacts with labor market frictions. In particular, our results suggest output standardization in response to mechanization. This standardization is valuable in environments with agency costs where family labor needs to be allocated to worker supervision, Bharadwaj (2015); Foster and Rosenzweig (2017). [2]

Finally, we related to the broader literature on the returns to technology adoption(Gollin et al., 2005; Foster and Rosenzweig, 2010b). Prior experiments in the agricultural sector have focused on the adoption intermediate inputs (Duflo et al., 2011; Suri, 2011), irrigation (Jones et al., 2020) and the role of learning (Conley and Udry, 2010). To our knowledge, this is the first study to estimate experimental returns to access to mechanization on labor use and agricultural productivity. Most estimates of returns to mechanization rely on panel studies where time-varying selection into mechanized practices is hard to control for (Pingali (2007); Takeshima et al. (2015). Indeed, when we compute the correlation between mechanization and productivity among treatment farmers we find a positive correlation between them, consistent with the findings in observational studies. Yet, we show that returns to mechanization are not statistically different from zero on average across farmers. This finding is consistent with Suri (2011)'s account of the seemingly puzzling low adoption of a highly profitable technology (hybrid) exploiting observational data. As in her study, we highlight heterogeneity across farmers in returns and cost to technology adoption. Because our experiment has randomized variation in the size of the subsidies across farmers, future versions of this manuscript will include returns from a binary (as currently presented) and from a continuous measure of treatment.

[2]Also related is Afridi et al. (2020), which uses soil characteristics to instrument for suitability for mechanization to estimate how mechanization affects labor use by gender.

2 Setting and Experimental Design

The experiment is a two-stage randomized controlled trial in 190 villages across eight districts in Karnataka.[3] The first stage of randomization is at the village-level, and the second is at the farm-level. Farmers were recruited into the experiment conditional on being interested in a lottery for subsidized mechanization rentals. After the baseline survey was administered, they were given a scratch card which either did not include a discount, included a discount for renting any equipment at the nearest custom hiring center, or included a rental discount and a cash grant. Farmers with subsidy vouchers could call the nearby CHC and request a rental service, and get a discount of up to the full subsidy amount off the rental price.The vouchers were valid between June and November 2019, spanning the main agricultural season (kharif) and part of the secondary season (rabi). All farmers, treatment and control, received a list of implements available at the nearest CHC, including the price for each implement, and the phone number of the nearest CHC. This was done to ensure that the information provided to all farmers in the intervention was identical. The exact amount of the rental discount varied, as did the cash grant. Small farmers (had cultivated less than 4 acres in 2018) received 2100 of rental subsidy, and large farmers (cultivated 4 acres or more in 2018) received 3500 of rental subsidy. These subsidies were split into two equal-amount vouchers, i.e. two 1050 for small farmers, that could not be combined in a single use. Farmers who received cash grants received half the value of the rental subsidy, and half the amount in cash (1050 in cash for small farmers and 1750 for large farmers). The size of each subsidy was calibrated to amount to approximately two rental hours of a rotavator/cultivator, which is the median use per transaction in the administrative data.

Villages were either assigned to the high intensity arm (70 villages), low intensity arm (70 villages), or the control group (60 villages). In each low-intensity village, 20 farmers were assigned to the control group, and 13 farmers to treatment. Out of the 13 farmers that

[3]The districts are Bellary, Chamarajanagar, Mysuru, Raichur, Yadagir, Hassan, Gulbarga and Koppal.

received the rental price subsidy, 6 farmers received an additional cash grants of equivalent amounts. In each high-intensity village, 20 farmers were in the control group and 34 farmers were in the treatment group. Out of the 34 farmers that received price subsidy, 16 farmers received additional cash grants. The control villages surveyed 20 farmers in each village. In total, about 7100 farmers were part of the intervention. More details on sample sizes and subsidy amounts can be found in Table B1.

3 Data and Empirical Strategy

We collected baseline data for about 7100 farmers in June and July 2019, and detailed endline data in February and March 2020. We survey farmers about land-holdings, baseline levels of assets and savings, agricultural input use, and agricultural income. In addition, we collected detailed data on labor use and wages by gender and whether family or hired labor was used across different stages of production (e.g. land preparation, planting, etc.). We also asked farmers all the tasks that different types of labor (family male labor, family female labor, hired male labor, hired female labor) engaged in. For the four members of households most involved in agricultural production, we additionally collected data on individual labor supply on the family farm during the season. Finally, we collected data on income from other sources, mainly working as agricultural labor on others' farms and nonagricultural income at the household level.

We combine this data with administrative data from our implementation partner, who maintains records of the universe of all rental service requests serviced by the CHCs in the state. In addition to using this data to measure our take-up, this data allows us to characterize the implements most used by farmers in the intervention, and how they vary from farmers who rent equipment from the CHCs during the normal course of CHC operations. Furthermore, they allow us to measure leakage, by checking whether farmers that were given

vouchers give them away.

Finally, we merge our data with weather information to control for temperature and rainfall. The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR) provides daily rainfall estimates at a spatial resolution of 0.25 degrees by 0.25 degrees (Sadeghi et al., 2019). Daily temperature data at the 0.5 degree level was obtained from the Climate Prediction Center (CPC) Global Temperature dataset.[4]

Due to fieldwork restrictions to minimize the risk of Covid-19 spread, the endline survey was only completed for about 5500 households. As we show in table 1, the take-up of mechanization on the platform is identical for households who were surveyed in the endline and those who were not, making it unlikely that treatment effects would vary for those households. Future drafts of this paper will include corrections for attrition in the treatment effects estimation.

Our main estimating equation is as follows:

$$y_i = \alpha + \beta \mathbb{1}[\text{Mechanization Voucher}_i] + \gamma \mathbb{1}[\text{Mechanization Voucher and Cash}_i] + \psi_1 y_{ib} + \psi_2 X_i + \epsilon_i \quad (1)$$

where y_i is the outcome of interest for farmer i, and $\mathbb{1}[\text{Mechanization Voucher}_i]$ is a binary variable that takes the value 1 if the farmer received a subsidy voucher for mechanization rental, and is 0 otherwise. $\mathbb{1}[\text{Mechanization Voucher and Cash}_i]$ is a binary variable that takes the value 1 if the farmer received both a subsidy voucher and a cash transfer, and is 0 otherwise. y_{ib} denote baseline controls, wherever available. X_i is a vector of controls containing village-level weather: monsoon rainfall and mean monsoom temperature, and land area cultivated (results are robust to the omission of these controls). β identifies the impact

[4]CPC Global Temperature data by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their Web site at https://psl.noaa.gov/.

of being given a rental subsidy voucher, and γ the additional effect of cash conditional on being given the subsidy voucher. Intent to treat (ITT) estimates are presented throughout the paper, though as discussed in the next section, Table 1 present take-up estimates to allow us to compute the Treatment on the Treated (TOT) estimates. Standard errors are clustered at the village-level.

4 Experimental Results

4.1 Mechanization Use

4.1.1 Take-up of Mechanization from Custom Hiring Centers

Our primary measure of take-up is a binary variable that takes the value 1 if we match a farmer's phone number to the transactions in the CHC data platform at any point between June and September 2019, and 0 otherwise.[5] Table 1 presents the results for take-up. Being assigned to the rental voucher treatment increases the probability that a farmer rents from the CHC during the intervention period, by 30 percentage points, a highly statistically significant effect. These results are identical when restricting the sample to those farmers for whom the endline survey was completed. Cash transfers have a small negative marginal effect on this outcome.

Table 2 presents heterogenous effects by land area. Larger farmers have a higher take-up rate, with one additional acre cultivated increasing the probability of renting from the CHC by 2 percentage points. As in Table 1, the effects are precisely estimated. Cash transfers do not impact take-up, and the results are not dependent on land cultivated.

Table B2 presents results separately for spillover farmers i.e. farmers who did nor receive either treatment, but were in treated villages. In this regression, farmers in control villages

[5]Alternative measures, that use phone number as well as name matching, yield identical treatment effects.

are the omitted group. The probability they rent from the CHC rental market is less than one-tenth the direct treatment, indicating that spillover effects were extremely small. Given this, we follow our pre-analysis plan and pool all control farmers for all analysis.

Table 1: Take-Up

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.316****	0.334****	0.318****	0.339****
	(17.86)	(17.09)	(16.86)	(16.12)
1(Cash and Mechanization)		-0.0374**		-0.0415**
		(-2.41)		(-2.55)
Observations	6713	6609	5332	5239
Endline Survey Only			X	X

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2: Take-Up by Land Size

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Treatment)	0.258****	0.289****	0.251****	0.283****
	(11.28)	(11.07)	(10.60)	(10.12)
1(Mechanization) X Baseline Area (Acres)	0.0191****	0.0146***	0.0220****	0.0179***
	(3.85)	(2.60)	(4.12)	(2.82)
Baseline Area (Acres)	0.00170	0.00153	0.000436	0.000182
	(0.99)	(0.89)	(0.21)	(0.09)
1(Cash and Mechanization)		-0.0660*		-0.0672*
		(-1.95)		(-1.80)
1(Cash) X Baseline Area (Acres)		0.0107		0.0101
		(1.14)		(0.93)
Observations	6713	6609	5332	5239
Endline Survey Only			X	X

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.1.2 Overall Mechanization Rental

To understand whether rental vouchers increase participation in the CHC rental market by merely substituting mechanization rental from informal markets, or they increase over-

all mechanization, we rely on survey data. We asked farmers about hours rented for each implement at different stages of production. We standardize all implement-wise hours (by subtracting by the mean and dividing by the standard deviation), and add up all standardized implement-wise hours. This allows us to aggregate across hours rented in of different implements, which otherwise vary widely (the standard deviation of the number of hours rented across different implements varies from 0.03 to 6 hours). This variable comprises our total mechanization rental variable. Our mechanization rental index is this variable per acre, and we take the inverse hyperbolic sine to dampen the effect of outliers (unlike the log function which has a similar function, it allows for negative values). We similarly standardize this variable to allow us to interpret the effect of treatment in terms of standard deviations of the dependent variable.

Results are presented in Table 3. The offer of a rental voucher increases mechanization by about 0.09 standard deviations (TOT of about 0.27 standard deviations). The effect sizes are relatively modest, but imply that the voucher treatment increased overall mechanization use. The effects are not different by land cultivated, implying that while larger farmers are more likely to use the voucher, the increase in mechanization use per acre is not greater for them.

Table 3: Mechanization Index Treatment Effects

	(1)	(2)	(3)	(4)
	IHS(Mechanization Index)			
1(Mechanization)	0.0870**	0.0954**	0.101	0.157*
	(2.39)	(2.34)	(1.28)	(1.80)
Baseline Area (Acres)	0.100****	0.100****	0.103****	
	(7.92)	(7.91)	(8.23)	
1(Cash and Mechanization)		-0.0202		-0.139
		(-0.48)		(-1.54)
1(Mechanization) X Baseline Area (Acres)			-0.00667	-0.0203
			(-0.40)	(-1.14)
1(Cash and Mechanization) X Baseline Area (Acres)				0.0370*
				(1.81)
Observations	5251	5251	5317	5317

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.2 Labor

As discussed in section 1, a primary impact of mechanization on agriculture is its impact on labor use. To identify these effects, we consider the number of workers per acre for four types of labor – family male labor, family female labor, hired male labor, and hired female labor. Results are presented in tables 4 and 5. Table 4 shows that the pooled treatment effect indicates a negative effect for family labor and a positive effect for hired labor. Family male labor declines by about 5.5 percentage points and family female labor by about four percentage points. In contrast, hired labor increases by about seven percentage points for men and about 3.5 percentage points for women. Table 5 shows that the effects separately by whether the treated farmer received only mechanization or both cash and mechanization, where the coefficient on the variable $\mathbb{1}$[Cash and Mechanization] measures the income effect. Mechanization reduces male family labor by about six percentage points, with cash transfers having no effect. Cash also does not affect hired male hired labor but mechanization increases hired male labor in particular. Cash increases female hired labor.

Why do the effects of mechanization vary by family vs. hired labor and by gender? Table 7 shows that tasks performed by different types of labor vary substantially. In particular, the survey asked respondents to list *all* tasks ever performed by different types of labor, namely, by family male labor, family female labor, hired male labor, and hired female labor. It is therefore a very liberal measure of task specialization, in that even if a type of labor engages in a particular task for a very small portion of time, that task would be included in their tasks description. Table B12 presents a more conservative measure, namely, which tasks listed first for the different labor types, and shows similar patterns. In particular, supervision is primarily conducted by male family labor, followed to a much lesser extent by female family labor. Several other tasks are gendered rather than segregated across family versus nonfamily labor – for instance, weeding and transplanting are primarily performed by women, whereas land preparation and manure application are primarily done by men. This is consistent with prior work (e.g. Bharadwaj (2015)) that illustrates the role of family size (which impacts the availability of labor with low or no contracting frictions) in hiring labor. These frictions facilitate task specialization by type of labor.

Tables B7 to B11 present results for labor used for acre separately for each stage of the production process – land preparation, planting, plant protection, harvesting, and harvest processing. Consistent with the model, the stage of production that is actually mechanized i..e. land preparation sees a decrease in male family labor and an increase in hired male labor. Land preparation is also a primarily a task done by males as shown in Table 7, so the pattern of increased male hired labor is consistent with this.

Table 4: Types of Labor: Treatment Effects

	(1)	(2)	(3)	(4)
	Ln(Family Males)	Ln(Famiy Females)	Ln(Hired Males)	Ln(Hired Females)
1(Mechanization)	-0.0559**	-0.0406*	0.0719**	0.0364
	(-2.59)	(-1.87)	(2.32)	(1.07)
Observations	4476	4485	4465	4477

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5: Types of Labor: Treatment Effects Separately by Cash vs. Mechanization

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	0.0178	0.00134	0.0327	0.0674*
	(0.86)	(0.05)	(0.83)	(1.91)
1(Mechanization)	-0.0636***	-0.0412*	0.0579*	0.00754
	(-2.67)	(-1.83)	(1.72)	(0.20)
Observations	4476	4485	4465	4477

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 6: Types of Labor: Treatment Effects by Area

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	0.0496	0.0247	0.0888	0.137*
	(1.10)	(0.41)	(1.11)	(1.80)
1(Mechanization)	-0.0863**	-0.0112	0.0126	0.0847
	(-2.32)	(-0.25)	(0.19)	(1.23)
1(Cash and Mechanization) X Baseline Area (Acres)	-0.00978	-0.00836	-0.0170	-0.0244
	(-0.92)	(-0.61)	(-0.96)	(-1.31)
1(Mechanization) X Baseline Area (Acres)	0.00676	-0.00941	0.0135	-0.0242
	(0.87)	(-1.01)	(0.96)	(-1.45)
Baseline Area (Acres)	-0.0855****	-0.0807****	-0.123****	-0.0854****
	(-12.26)	(-10.68)	(-11.41)	(-6.89)
Observations	4476	4485	4465	4477

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 7: Tasks Ever Performed by Types of Labor

Sno.	Task	Family Male	Hired Male	Family Female	Hired Female
1	Supervision of farm labor	67.29	16.49	25.96	7.49
2	Sourcing inputs	51.7	33.42	19.18	16.28
3	Land preparation	64.77	60.63	29.07	28.28
4	Manure application	62.17	68.63	42.53	46.07
5	Sowing seed	44.79	51.14	58.5	63.42
6	Transplanting	36.02	40.89	63.69	69.96
7	Chemical Fertilizer Application	50.49	53.86	38.77	43.01
8	Hand Weeding	34.02	36.95	70.57	77.17
9	Interculture	56.95	54.29	46.68	47.75
10	Plant protection	40.26	36.81	22.88	22.73
11	Irrigation	34.67	28.71	13.47	14.24
12	Watching	45.65	25.6	15.97	10.32
13	Harvesting	26.34	29.65	23.31	27.23
14	Threshing	13.3	13.79	6.42	7.19
15	Marketing	16.81	3.52	1.65	0.99
16	Other	1.33	2.62	3.49	1.78

4.3 Productivity

In this section, we show treatment effect estimates of the impacts on productivity. Cash has the ability to relax liquidity constraints, and may crowd in input intensification and increase productivity. We have two measures of productivity – total revenue per acre (which is only defined if a farmer sold output) and profit per acre, which is defined for all households. We measure profit via a survey question which asks farmers how much money they had left over from farming income after paying all expenses.[6] Results are presented in Tables 8 and 9– the former pool both treatments, and the latter present results separately by treatment arms. We find that neither treatment impacts productivity on average. However, the effects of mechanization are greater for larger land sizes, and the effects are statistically significant at the 1% level. Table 9 shows that these effects are driven solely by the rental voucher subsidy, with no additional effects for cash transfers. Alternative measures of productivity where we measure revenues and profits per worker rather than per acre of land are presented in Tables

[6]Alternative measures that subtract input costs elicited from total revenues give similar results.

B4 and B5, and are consistent with these results.

These results are noteworthy for two reasons. First, they show that mechanization use alone does not significantly increase productivity on small farm sizes such as those in our data (the average land cultivated in the sample is 2.5 acres), but as hypothesized in prior work using observational data, greater land sizes benefit more from mechanization use (Foster and Rosenzweig, 2017). Second, they show that any changes to input use, or labor supply by family workers are not driven by changes in income on average – rather, we can interpret these as the effects of mechanization alone on the agricultural production process.

Table 8: Productivity Per Acre: Treatment Effects

	(1)	(2)	(3)	(4)
	Log(Revenue/Acre)		IHS(Profit/Acre)	
1(Mechanization)	0.0204	-0.0769	-0.129	-1.055**
	(0.26)	(-0.63)	(-0.46)	(-2.48)
Baseline Area (Acres)	-0.0770****	-0.0916***	0.283****	0.143**
	(-4.16)	(-3.32)	(4.73)	(1.98)
1(Mechanization) X Baseline Area (Acres)		0.0314		0.303***
		(0.87)		(3.17)
Observations	4548	4548	5332	5332

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 9: Productivity Per Acre: Treatment Effects by Cash vs. Mechanization

	(1)	(2)	(3)	(4)
	Log(Revenue/Acre)		IHS(Profit/Acre)	
1(Cash and Mechanization)	0.0966	0.167	0.411	0.357
	(1.00)	(0.93)	(1.29)	(0.68)
1(Mechanization)	-0.0208	-0.153	-0.303	-1.245**
	(-0.25)	(-1.13)	(-0.94)	(-2.46)
Baseline Area (Acres)	-0.0760****	-0.0916***	0.288****	0.143**
	(-4.14)	(-3.33)	(4.79)	(1.98)
1(Cash and Mechanization) X Baseline Area (Acres)		-0.0198		0.0419
		(-0.45)		(0.36)
1(Mechanization) X Baseline Area (Acres)		0.0410		0.300***
		(1.05)		(2.72)
Observations	4548	4548	5332	5332

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 10: Raw Materials Treatment Effects

	(1)	(2)	(3)	(4)
	Log(Raw Materials Expenditure/Acre)			
1(Mechanization)	-0.000856	-0.00968	0.0274	-0.0419
	(-0.02)	(-0.18)	(0.34)	(-0.42)
Baseline Area (Acres)	-0.162****	-0.162****	-0.157****	
	(-13.05)	(-12.87)	(-8.33)	
1(Cash and Mechanization)		0.0209		0.177*
		(0.40)		(1.65)
1(Mechanization) X Baseline Area (Acres)			-0.0181	0.00151
			(-0.72)	(0.05)
1(Cash and Mechanization) X Baseline Area (Acres)				-0.0550*
				(-1.70)
Observations	4594	4594	4594	4594

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.4 Input Expenditures

In addition to changing the pattern of labor use, mechanization may impact input intensification, either directly or via its impact on labor use. Table 10 tests this hypothesis, including

presenting heterogeneous effects by land size. Input expenditures are the sum of expenditures on seeds, irrigation, fertilizer, manure, animal labor, and other plant protection inputs. The outcome variable is the log of input expenditures per acre. We do not find effects of either treatment on input expenditure, and the effects do not vary by land area.

Table 11 shows effects on hired labor expenditure (these comprise all labor expenditures, since family labor is unpaid, in that the 99th percentile of wages paid to family labor, male or female, is 0). Consistent with the effects on hired labor use, hired labor expenditure increases, with the treatment effects on the voucher only arm showing an 18 percentage point increase in hired labor expenditure. The effects do not vary by land area, which is consistent with the results on mechanization use per acre. Thus, increased access to mechanization increases hired labor expenditure, with no change in raw materials.

Table 11: Hired Labor Expenditure Treatment Effects

	(1)	(2)	(3)	(4)
	Log(Hired Labor Expenditure/Acre)			
1(Mechanization)	0.211***	0.177**	0.227	0.166
	(2.67)	(2.04)	(1.58)	(1.03)
Baseline Area (Acres)	-0.0904****	-0.0894****	-0.137****	
	(-5.06)	(-4.96)	(-5.44)	
1(Cash and Mechanization)		0.0784		0.136
		(0.92)		(0.84)
1(Mechanization) X Baseline Area (Acres)			0.0171	0.0266
			(0.52)	(0.74)
1(Cash and Mechanization) X Baseline Area (Acres)				-0.0220
				(-0.49)
Observations	4335	4335	4335	4335

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.5 Nonagricultural Income

Finally, we test whether the unpaid male family labor released from the farm by increased mechanization is reallocated to other sectors by examining the effects on household-level

nonagricultural income. Table 12 presents the results. We find no effects of either mechanization or cash on household-level nonagricultural income – this implies that at least in the short run, households substitute into leisure or unpaid home production instead of taking up non-farm work.

Table 12: Household-Level Non-Agricultural Income: Treatment Effects

	(1)	(2)	(3)	(4)
	1(Any Non-Agricultural Income)		Log(Non-Agricultural Income)	
1(Mechanization)	-0.000227	-0.00454	-0.0190	-0.0395
	(-0.01)	(-0.25)	(-0.12)	(-0.23)
1(Cash and Mechanization)		0.00571		0.0254
		(0.32)		(0.16)
Observations	5332	5468	5332	5468

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

5 A model of farming and mechanization

In this section, we present a model that allows us to interpet the channels through which we observe the treatment effects from the experiment. The economy is populated by a continuum of heterogeneous farming households comprised by f family workers. Family workers elastically supply labor for farming activities. Each household is endowed with one plot of land of varying size, l.

Farming entails two processes: land preparation and planting, *preparation* henceforth; and plant protection, harvesting and processing, *harvest* henceforth. Agricultural output is a Leontief aggregator of the output from these two processes. Farmers use land, capital and labor to produce. Whereas both capital and labor are used to complete these processes, our empirical findings suggest that the intervention affected mechanization practices at the preparation stage only. Therefore, to simplify the exposition, we assume that harvesting activities are only performed with labor. Hired labor is heterogeneous could be supervised or unsupervised. Certain tasks in farming are more likely to be supervised (by a family

member) and workers are more productive if supervised. Other tasks are more likely to have hired labor working unsupervised.

Farmers take as given input prices, including that of labor and the rental price of capital. Through the lens of this model, our intervention generated two exogenous shifts. First, it reduced the rental cost of capital for farmers in the treatment group. Second, it shifted household incomes through a cash transfer. Because the cash transfer generated no additional movement in mechanization or labor choices we abstract from this in the model.

Importantly, the model illustrates how our experimental design allows us to identify key parameters of interest, such as the returns to mechanization and the elasticity of substitution between capital and labor.

In subsequent versions of the manuscript we will include a welfare analysis of the intervention.

5.1 Farming

To illustrate the main channels through which a subsidy for mechanization services affects labor, assume no differences in family workers across gender.

The adoption of mechanized labor simplifies tasks and standardizes the effort for a particular task, easing needs for worker supervision. But mechanization is not amenable for all tasks and for all terrains. The introduction of a subsidy like the one implemented in our randomized design frees up resources towards input intensification, in this case, labor for areas that are hard to reach by machines or activities that cannot be readily performed by the machine, e.g. moving piles of weed to trucks, moving inputs into the field.

Let the size of a plot be l, capital services k, hired labor n_h and family labor n_f. We think of family labor as mostly engaged in supervision activities (consistently with the empirical evidence). Output from the preparation stage, y^P, is a Cobb-Douglas function of

unsupervised labor, land, and tasks, x_i that can be either be performed by a machine or by supervised labor.

$$y^P = \left(\int_{i=0}^{1} x_i^{\gamma_i} \right)^{\alpha} l^{\alpha_l} n_h^{\alpha_h}.$$

where $\int_{i=0}^{1} \gamma_i = 1$, $\alpha_l = 1 - \alpha_h - \alpha - \alpha_f$ and

$$x_i = \frac{\min\{\bar{l} - l, 0\}}{\bar{l} - l} a_k(i) k(i) + n_f^{\frac{\alpha_f}{\alpha}} a_s(i) n_s(i)$$

We assume that farmers can only take advantage of mechanization if the hold a minimal scale $\bar{l}$. This feature is consistent with the observed higher mechanization for larger plot holders at baseline. We assume overall constant returns to scale but because land is assumed a fixed factor, the profits of farming are indeed the returns to land. Family workers supervise hired labor in the tasks that could potentially be mechanized. The productivity of supervised labor depends on the effort of family supervision n_f. We index tasks by i and assume the following pattern of comparative advantage in labor and capital,

Assumption 1 $\frac{a_s(i)}{a_k(i)}$ are continuously differentiable and increasing in i.

That is, capital is relatively more productive in tasks that have a lower index. Because supervised labor and capital are perfect substitutes, there will be full specialization in tasks. Let I be the measure of tasks that are mechanized.

Output in the harvesting stage,y^H, is a Cobb-Douglas aggregator labor and land. In this case, we assume that labor related tasks, j, can be performed with either supervised labor, or unsupervised labor.

$$y^H = \left(\int_{j=0}^{1} x_j^{\gamma_j} \right)^{\alpha} l^{\alpha_l}.$$

where $\int_{j=0}^{1} \gamma_j = 1$ and

$$x_j = n_f^{\frac{\alpha_f}{\alpha}} b_s(j) n_s(j) + b_h(j, I) n_h(j)$$

where $\alpha + \alpha_f + \alpha_l = 1$. We assume that supervised labor has a comparative in lower indexed

tasks,

Assumption 2 $\frac{b_h(j,I)}{b_s(j)}$ are continuously differentiable and increasing in j.

To rationalize the impact that standardization at the preparation stage (due to mechanization) has on harvesting activities, we further assume

Assumption 3 $b_h(j,I) = \bar{b}_h(j) + I$ is an increasing function of the measure of tasks performed by the machine in the preparation stage, I.

Final output in farming is simply

$$Y = \min\left[y^P, y^H\right]$$

5.2 Allocation

In what follows we assume farmers behave competitively taking prices of inputs and output (normalized to 1) as given.

Preparation stage

The optimal allocation of inputs to tasks given prices is such that the value of the marginal product for a supervised worker is the same irrespective of the task it performs, and the same is true for capital service,

$$p(i)n_f^{\frac{\alpha_f}{\alpha}}a_s(i) = w_s, \qquad (n_s(i))$$

$$p(i)a_k(i) = r, \qquad (k(i))$$

where $p(i)$ is the price of output for task i.

The optimality conditions across tasks require

$$\nu\alpha\gamma_i\frac{y^P}{x_i} = p(i) \qquad (x_i)$$

An implication of these conditions is that the quantities of labor and capital in each task

are proportional to each other. Assume further that γ_i are all identical. It follows that the expenditure shares should be equalized across inputs. This feature combined with the marginal conditions implies that factor allocations are the same across tasks produced by the same input. Therefore, if I is the threshold for mechanization, allocations are

$$n_s(i) = \frac{n_s}{1-I}$$

$$k(i) = \frac{k}{I}$$

where n_s, k are the amounts of supervised labor and capital serviced hired by the farm.

Using the properties of the allocation, we can rewrite output at the preparation stage as

$$y^P = A^P \left(\frac{k}{I}\right)^{\gamma_I \alpha} \left(\frac{n_s}{1-I}\right)^{(1-\gamma_I)\alpha} n_f^{\alpha_f(1-\gamma_I)} l^{\alpha_l} n_h^{\alpha_h}.$$

where $A^P = \bar{a}_k(I)\bar{a}_s(I)$ is an endogenous productivity term, where $\bar{a}_k(I) \equiv \left(\prod_{i=0}^{I} a_k(i)^{\gamma_i}\right)^{\alpha}$, $\bar{a}_s(I) \equiv \left(\prod_{i=1-I}^{1} a_s(i)\right)^{\alpha}$ and $\gamma_I = I\gamma$ is the factor share associated to the tasks being automated. Not that the share of family (supervision) labor decline with mechanization.

Given the above technology, we can solve for the optimality conditions for family labor, supervised and unsupervised labor, capital and land as a function of the threshold I. Standard optimality conditions yield the key predictions for input allocations (see Appendix A).

Harvesting stage The optimal allocation of inputs to tasks given prices is such that the value of the marginal product for a supervised worker is the same irrespective of the task it performs, and the same is true for unsupervised labor,

$$p(j) n_f^{\frac{\alpha_f}{\alpha}} b_s(j) = w_s, \qquad (n_s(j)^H)$$

$$p(j) b_h(j, I) = w_h, \qquad (n_h(j)^H)$$

where $p(j)$ is the price of output for task j.

The allocations are similar to those in the preparation stage. In particular, output can be described as

$$y^H = A^H \left(\frac{n_s}{1-J}\right)^{\gamma_J \alpha} \left(\frac{n_h}{1-J}\right)^{(1-\gamma_J)\alpha)} n_f^{\alpha_f \gamma_J} l^{\alpha_l}.$$

where $A^H = \bar{a}_h(J)\bar{a}_s(I)$ is an endogenous productivity term, where $\bar{a}_s(J) \equiv \left(\prod_{j=0}^{J} a_s(j)^{\gamma_i}\right)^{\alpha}$, $\bar{a}_h(J) \equiv \left(\prod_{i=1-J}^{1} a_h(j)\right)^{\alpha}$ and $\gamma_j = J\gamma$ is the factor share associated to the tasks performed by supervised labor. Standard optimality conditions yield the key predictions for input allocations (see Appendix A).

5.3 Main experimental findings through the lens of the model

Fact 1 *Take up is higher for larger farmers* This is a direct consequence of the minimum scale requirements for capital usage.

Fact 2 *The subsidy induces mechanization.* Higher mechanization can be interpreted through the lens of the model as a higher share of tasks being mechanized. Indeed, combining equations $n_s(i)$, $k(i)$ we obtain the marginal condition for mechanized tasks as a function of prices and input demands.

$$\frac{w_s}{r} = \frac{n_f^{\frac{\alpha_f}{\alpha}} a_s(i)}{a_k(i)} \tag{2}$$

Therefore, when the price of capital falls due to the subsidy, the marginal mechanized task is higher, $I^s > I$ under Assumption 1.

Note that the threshold for mechanization is independent of the level of the capital-labor ratio, and a decreasing function of the amount of family labor n_f.

Fact 3 *mechanization hours increase on average (for those taking the subsidy) and there are no systematic differences in size.* Mechanization hours can be mapped to the amount

of capital services demanded by the farm, k. The implied capital labor ratios across farm follow from the optimality conditions, n_s and k,

$$\frac{w_s}{r} = \frac{k}{n_s}\frac{1-\gamma_I}{\gamma_I}$$

If all farms display the same degree of task mechanization I and factor shares γ_I, capital labor ratios are equalized across farms. The levels (or scales) are different through land size differences.

Capital-land ratios can be solved from the optimality condition for capital, equation (k), and the optimal input ratios. Taking logs, computing the total differential and rearranging, we obtain the change in the capital per acre given a change in the cost of capital.

$$\frac{d(k/l)}{dr}\frac{r}{(k/l)} = \frac{(\alpha+\alpha_f)(1-\gamma_I)}{\alpha_l - 1}\frac{d\gamma_I}{dr}\frac{r}{\gamma_I} + (1-\gamma_I)\frac{\alpha}{\alpha_l}\frac{d\frac{(1-\gamma_I)}{\gamma_I}}{dr}\frac{r}{\frac{(1-\gamma_I)}{\gamma_I}} \tag{3}$$

Therefore, the elasticity of the capital to land ratio to the price of capital is a function of the elasticity of the share of mechanized tasks to the cost of capital. The share γ_I moves as a function of the mechanization threshold, I which is in turn a function of the profiles of comparative advantage. If these are identical across farms we should expect no differences in the elasticity of mechanization per acre across farms of different sizes. Notice also, that the sign of the RHS is negative, indicating that capital to land ratios indeed increase as the price of capital falls.

It is possible to interpret the elasticity on the LHS as the returns to subsidizing the rental cost of capital. One stark prediction of the model is that as farmers become more mechanized, those returns fall, ceteris paribus. The reason is that the set of tasks that could potentially be completed by a machine are indeed bounded. The second prediction of the model that is useful in interpreting the expression for returns is that

the elasticity of the relative income shares for mechanizable tasks to the rental cost of capital (the last term in equation 3) equalizes the elasticity of the family labor to capital ratio to the cost of capital. This is an important result because it directly links the behavior of family labor (which is observable, unlike the tasks shares) to the return to capital.

Fact 4.a *Family labor falls at preparation* A lower cost of capital $r^s < r$ induces mechanization, higher I. Ceteris paribus, the optimality condition n_f induces lower family labor. The reason is that the marginal product of family labor falls when the degree of mechanization increases.

Fact 4.b *Family labor falls at harvesting* This is a direct consequence of Assumption 3 and the production structure at the preparation stage. Combining equations $n_s(j)^H$, $n_h(j)^H$ we obtain the marginal condition for tasks performed by supervised labor as a function of prices and input demands.

$$\frac{w}{w_s} = \frac{b_h(j, I)}{n_f b_s(j)}$$

If a farm became more mechanized at the preparation stage, the return to supervised labor increases. Assumption 3 then implies that a lower portion of the tasks shall be performed with supervised labor, $J' < J$, and that encompasses lower family labor demand. The ratio of the optimality conditions, equation n_f^H and n_h^H yield the result

$$\frac{w}{w_f} = \frac{n_f}{n_h}\frac{(1-\gamma_J)}{\gamma_J}$$

Fact 5 *Labor hired for preparation increases* This is a direct consequence of the gains in productivity from cheaper capital. The optimality condition for hired labor n_h implies that the marginal product is higher, and therefore the farm desires more of those workers.

Fact 6 *Profitability does not increase on average* Given that land is the fixed factor, profits

equal the returns to land. Also, given the Leontief production structure, it is enough to compute profitability at a single stage of production. In this case, we focus on the procession stage.

From the optimality conditions of the processing stage we can compute the change in input ratios from a change in the rental price of capital. Given the Cobb-Douglas structure, these elasticities are all unitary. Therefore, taking logs to the expression for output per acre and totally differentiating we obtain

$$\frac{d\frac{y^P}{l}}{dr}\frac{r}{\frac{y^P}{l}} \approx \underbrace{\frac{dA^P}{dr}\frac{r}{A^P}}_{task-productivity} + \underbrace{(1-\gamma_I\alpha_f)\frac{dk}{dr}\frac{r}{k}}_{intensive-mech} - \underbrace{\alpha_f\frac{d\gamma_I}{dr}\frac{r}{\gamma_I}}_{extensive-mech} \tag{4}$$

Equation 4 highlights the key channels through which mechanization affects productivity. The first one is the *task productivity* term which directly relates to the comparative advantage of completing a task with machines relative to supervised labor. The second one is the *intensive-mechanization* term, which is standard in a neoclassical productivity structure where price declines generate input intensification. The third one is the *extensive-mechanization* term, which reflects another dimension of input intensification, through the change in the tasks performed by different factors. The sign of the extensive mechanization effect is unambiguously positive (i.e. more tasks get mechanized), the sign of the intensive-mechanization effect is unambiguously negative because the marginal product of capital declines with higher capital intensity. Finally, the sign of the productivity effect could be positive or negative. The level and the slope of the profile of comparative advantage is key for this result. If the comparative advantage of capital degrades relatively quickly (on the task dimension), the threshold I moves little due to the rental rate subsidy and productivity does not improve. If instead the comparative advantage of capital is relatively stable, the threshold I moves a lot from the rental rate subsidy decline and productivity improves. In the first case,

note that a rapid decline in the comparative advantage is equivalent to a decline in the marginal product of capital.

Interestingly, the LHS of equation 4 and the second term in the RHS of equation 4 are observable. The third term on the RHS can be inferred as residual from equation 3. Putting together these components would allow us to infer the effect on farm productivity (Hicks neutral) form our experiment. This is important because in a standard productivity estimation exercise, even absent measurement error considerations, this productivity term would show up as an exogenous and orthogonal residual to input shares. In our case, the residual is endogenous and depends on the implemented policy through the incentives to mechanization.

6 Conclusion

We provide the first available measures of the returns to mechanization from experimental evidence. We find no statistically significant positive returns on average, and higher returns to farmers with larger land-holdings. The measurement of the returns to adoption of mechanized practices is of first order relevance to understanding the effect of policies directed towards capital intensification on overall productivity. Evermore important when governments in the developing world are increasingly intervening to subsidy equipment purchases at large scale, or the development of capital rental markets altogether.

Importantly, we identify a key margin through which the returns to mechanization are realized, output standardization. Mechanization induces hiring of more workers and reduction of family labor in the farm. These movements are consistent with the presence of agency costs in labor markets. In addition, it suggest that mechanization impacts labor use in a nuanced way due to task specialization by different types of labor induced by agency costs. A model of task replacement and worker supervision can rationalize all of the experimental findings. Declines in the cost of capital induce capital-intensification along the intensive and extensive (task replacement) margins.

In subsequent versions of the paper, continuous treatment effects will be reported. This would allow us to fully quantify the return mechanization. We will also include adjustment for attitudes towards risk, which we measured at baseline. Finally, we will quantify each of the channels through which rental subsidies affect productivity as dictated by the model. This quantification is useful to assess the relative importance of different channels.

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A Allocations

Processing stage The optimality conditions with respect to input intake are

$$\alpha_h \frac{y^P}{n_h} = w \qquad (n_h)$$

$$\alpha_f (1-\gamma_I) \frac{y^P}{n_f} = w_f \qquad (n_f)$$

$$\alpha (1-\gamma_I) \frac{y^P}{n_s} = w_s \qquad (n_s)$$

$$\alpha \gamma_I \frac{y^P}{k} = r \qquad (k)$$

Harvesting stage The optimality conditions with respect to input intake are

$$\alpha (1-\gamma_J) \frac{y^H}{n_h} = w \qquad (n_h^H)$$

$$\alpha_f \gamma_J \frac{y^H}{n_f} = w_f \qquad (n_f^H)$$

$$\alpha \gamma_J \frac{y^H}{n_s} = w_s \qquad (n_s^H)$$

B Tables

Table B1: Details of Experimental Design

	High-Intensity Village (70 villages)		
Number of Treatment Farmers Per Village	Land Cultivated	Subsidy Amount (₹)	Cash Transfer (₹)
10	<4 acres	2100	0
9	<4 acres	2100	1050
4	<4 acres	1050	0
4	<4 acres	1050	1050
2	≥ 4 acres	3500	0
2	≥ 4 acres	3500	1750
1	≥ 4 acres	1750	0
1	≥ 4 acres	1750	1750

	Low-Intensity Village (70 villages)		
Number of Treatment Farmers Per Village	Land Cultivated	Subsidy Amount (₹)	Cash Transfer (₹)
4	<4 acres	2100	0
3	<4 acres	2100	1050
1	<4 acres	1050	0
1	<4 acres	1050	1050
1	≥ 4 acres	3500	0
1	≥ 4 acres	3500	1750
1	≥ 4 acres	1750	0
1	≥ 4 acres	1750	1750

All treatment and control villages have 20 control farmers each.

Table B2: Take-Up: Direct and Spillover Effects

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Treatment)	0.329****	0.349****	0.333****	0.356****
	(17.78)	(17.27)	(16.74)	(16.31)
1(Spillover)	0.0147**	0.0146**	0.0201***	0.0201***
	(2.29)	(2.29)	(2.86)	(2.86)
1(Cash and Mechanization)		-0.0423***		-0.0474***
		(-2.76)		(-2.97)
Observations	7129	7022	5468	5373
Endline Survey Only			X	X

t statistics in parentheses. Standard errors are clustered at the village-level. Baseline controls included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B3: Take-Up Up to Four Months Post-Intervention

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.00799***	0.00846**	0.00794**	0.00921**
	(2.75)	(2.41)	(2.56)	(2.36)
1(Cash and Mechanization)		0.000220		-0.00176
		(0.05)		(-0.35)
Observations	7129	7022	5468	5373

t statistics in parentheses. Standard errors are clustered at the village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B4: Productivity Per Worker: Treatment Effects

	(1)	(2)	(3)	(4)
	Log(Revenue/Worker)		IHS(Profit/Worker)	
1(Mechanization)	-0.00337	-0.164	-0.109	-0.728**
	(-0.05)	(-1.37)	(-0.53)	(-2.48)
Baseline Area (Acres)	0.128****	0.103****	0.280****	0.185****
	(6.70)	(3.84)	(6.58)	(3.52)
1(Mechanization) X Baseline Area (Acres)		0.0523		0.203***
		(1.53)		(2.89)
Observations	4508	4508	5227	5227

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B5: Productivity Per Worker Treatment Effects by Cash vs. Mechanization

	(1)	(2)	(3)	(4)
	Log(Revenue/Worker)		IHS(Profit/Worker)	
1(Cash and Mechanization)	0.0713	0.108	0.222	0.119
	(0.85)	(0.70)	(0.98)	(0.33)
1(Mechanization)	-0.0338	-0.216	-0.203	-0.804**
	(-0.44)	(-1.64)	(-0.86)	(-2.27)
Baseline Area (Acres)	0.129****	0.103****	0.282****	0.185****
	(6.75)	(3.84)	(6.63)	(3.52)
1(Cash and Mechanization) X Baseline Area (Acres)		-0.00803		0.0499
		(-0.20)		(0.59)
1(Mechanization) X Baseline Area (Acres)		0.0571		0.192**
		(1.56)		(2.34)
Observations	4508	4508	5227	5227

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B6: Mechanization Index Treatment Effects by Stages of Production

	(1) IHS (Mechanization Index) -Land Preparation	(2) IHS (Mechanization Index) - Planting	(3) IHS (Mechanization Ind -Harvesting
1(Cash and Mechanization)	0.00190	-0.00939	-0.00121
	(0.05)	(-1.47)	(-0.08)
1(Mechanization)	0.0731*	0.0102	0.0180
	(1.92)	(1.09)	(0.92)
Observations	5265	5171	5348

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B7: Types of Labor: Treatment Effects During Land Preparation

	(1) Ln(Family Males)	(2) Ln(Hired Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Fe
1(Cash and Mechanization)	-0.00492	-0.0228	-0.00671	0.00092
	(-0.52)	(-0.90)	(-0.57)	(0.05)
1(Mechanization)	-0.0271***	0.0374*	-0.00203	-0.0070
	(-3.07)	(1.92)	(-0.21)	(-0.44)
Observations	4476	4455	4484	4449

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B8: Types of Labor: Treatment Effects During Planting

	(1) Ln(Family Males)	(2) Ln(Hired Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Fe
1(Cash and Mechanization)	-0.00193	0.0489	-0.0300**	-0.019
	(-0.14)	(1.56)	(-2.56)	(-0.57)
1(Mechanization)	-0.0197	0.0206	-0.00648	0.0301
	(-1.63)	(0.84)	(-0.62)	(0.98)
Observations	4479	4467	4493	4472

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B9: Types of Labor: Treatment Effects During Plant Protection

	(1) Ln(Family Males)	(2) Ln(Hired Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Fe
1(Cash and Mechanization)	-0.0125	-0.0802***	-0.0390****	-0.0872
	(-0.94)	(-3.04)	(-3.38)	(-2.25)
1(Mechanization)	-0.0207*	0.0224	-0.00834	0.0050
	(-1.91)	(0.99)	(-0.77)	(0.16)
Observations	4476	4459	4494	4450

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B10: Types of Labor: Treatment Effects During Harvesting

	(1) Ln(Family Males)	(2) Ln(Hired Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Fe
1(Cash and Mechanization)	-0.000628	0.0723*	-0.0242*	-0.035
	(-0.05)	(1.86)	(-1.96)	(-0.93)
1(Mechanization)	-0.0244**	0.0277	-0.00792	0.0791*
	(-2.05)	(0.97)	(-0.76)	(2.45)
Observations	4480	4461	4493	4453

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B11: Types of Labor: Treatment Effects During Harvest Processing

	(1) Ln(Family Males)	(2) Ln(Hired Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Fe
1(Cash and Mechanization)	-0.00601	-0.00678	-0.0115	0.0099
	(-0.45)	(-0.21)	(-0.96)	(0.31)
1(Mechanization)	-0.0247**	0.0297	-0.0149	0.0247
	(-2.16)	(1.29)	(-1.58)	(1.06)
Observations	4484	4463	4485	4454

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table B12: Tasks First Listed Being Performed by Types of Labor

Sno.	Task	Family Male	Hired Male	Family Female	Hired Female
1	Supervision of farm labor	67.65	16.63	26.1	7.53
2	Sourcing inputs	8.19	21.41	8.05	10.75
3	Land preparation	15.92	34.53	13.76	16.81
4	Manure application	3.76	13.36	16.98	20.78
5	Sowing seed	1.14	4.76	16.67	22.47
6	Transplanting	0.7	2.12	9.63	12.45
7	Chemical Fertilizer Application	0.28	1.59	0.84	1.46
8	Hand Weeding	0.15	0.63	3.74	5.58
9	Interculture	0.63	1.16	0.65	0.28
10	Plant protection	0.1	0.23	0.12	0.05
11	Irrigation	0.1	0.38	0.02	0.07
12	Watching	0.08	0.27	0.1	0.03
13	Harvesting	0	0.3	0.02	0.07
14	Threshing	0	0	0.03	0
15	Marketing	0.03	0	0.02	0
16	Other	1.27	2.61	3.28	1.67