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 estimates the returns to mechanization and its impact on labor combining a randomized controlled experiment and a structural model of task-replacement. Treatment farmers were given subsidy vouchers to access agricultural equipment from nearby custom hiring centers (CHC). In addition, 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 0.13 standard deviations (a treatment on the treated effect size of 0.36 standard deviations). We find no significant improvements in output per acre due to mechanization on average. However, family labor decreases in response to the subsidy in capital, and farmers reduce hired labor in all farming processes, including those not directly affected by mechanization. We document that family labor is mostly occupied in supervision activities, and that their lower engagement in farming is associated with higher non-agricultural income. The decline in supervision labor and the decline in hired labor across farming processes are interpreted as evidence of output standardization, which is beneficial in the presence of contracting frictions. We use key elasticities from the experiment and our structural model to infer the marginal return to mechanizable tasks, which we estimate at 36% per season, and to estimate the relative importance of different channels in response to mechanization.

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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 likely more 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). Mechanization is potentially transformative of the production process through its effects on labor and productivity. Indeed, governments in the developing world are increasingly intervening in the agricultural sector to subsidize mechanization and modernize the sector. But to date, little is known about the magnitude of the returns to mechanization, the channels through which mechanization shifts labor and productivity, and importantly, how those shifts are mediated by frictions that are pervasive in the developing world, such as contracting frictions.

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. 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. One challenge of identifying the effect of mechanization on productivity and its returns 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 we circumvent this problem.

The randomized controlled trial covered 7,100 farmers across nearly 200 villages in the state of Karnataka. Farmers were given a lottery for subsidy vouchers to access approximately 2 hours worth of agricultural equipment rental services from a nearby custom hiring center (CHC).[1] Farmers could rent any equipment available at the CHC, including tractors, rotavators, and cultivators. 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 collected 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. Importantly, we collected information on task engagement for different members of the household, as well as for hired labor. 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 merely 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 responsible for higher take-up. Importantly, the voucher treatment increases overall mechanization hours,

[1] The size of the voucher was calibrated to match the median usage of rental equipment in past seasons.

with an intent to treatment effect size of about 0.13 standard deviations (a treatment on the treated effect size of 0.36 standard deviations). We find no differential response of mechanization hours per acre between large and small land-holdings. 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. A direct task replacement effect of capital intensification is typically labor saving. An indirect effect of mechanization on productivity is typically labor pulling. The overall effect of a capital subsidy on labor depends on the relative strength of these channels.[2] Our results indicate that farmers hire less workers for production by about 8 percentage points. Therefore, the substitution effect is stronger than the productivity effect. Indeed, while the point estimate for the change in productivity in response to treatment —either measured as revenue per acre or profits per acre— is positive on average, the estimate is not statistically different from zero.

Family labor supply and hired labor declines both during land preparation, when mechanization use increases; and harvesting, when treatment has no effect on mechanization. The magnitude of the effects are quite different by types of labor, with the greatest effect on hired labor. Mechanization reduces male family labor use by about 0.13 workers per acre over the season, whereas for hired male workers, the impact is much larger, about 0.425 workers per acre. Since family labor is mostly occupied in supervision activities, we interpret the decline in supervision labor and the persistent effect of mechanization on hired labor as evidence of output standardization, which is beneficial in the presence of contracting frictions. Moral hazard problems are ubiquitous in agricultural labor, and therefore, by increasing output observability, mechanization eases these problems. Hence, it has direct implications for the span of control of family labor on the farm, — the solution to allocating productive resources over managers of different ability Manne (1965); Lucas (1978). The role of mechanization

[2] The effect is characterized by the cross-price elasticity of labor demand, which is a function of a pure substitution effect (labor saving) and a scale effect (labor pulling), Hicks (1932).

in easing moral hazard problems to free up managerial resources is a novel channel for the transformative role of capital intensification in rural economies. Indeed, we find that while family labor pulls back from their supervision role, non-agricultural income for treatment households increases by 41% relative to control. This is consistent with labor reallocation in response to capital-deepening in agriculture, as stressed by an extensive literature on structural transformation, Acemoglu and Guerrieri (2008); Bustos et al. (2020).

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). This "underutilization" of a technology should be reflected in higher returns, i.e. unrealized gains Foster and Rosenzweig (2010a). Estimating (marginal) returns to mechanization is a challenging task because its adoption induces shifts in the demand of other inputs and it is likely to change total factor productivity altogether, i.e. the output change that is not explained by changes in observable inputs. Hence, even after randomizing the change in capital through an experimental design, treatment is not a valid instrument for capital because it is correlated with residuals. To make progress in the estimation of these returns, we pose a structural model where farming is a collection of processes. Within each process a number of tasks can be produced by machines or supervised labor. The effects of treatment on take up, mechanization hours and labor allocation are readily rationalized by this simple framework. The optimal factor allocation as predicted by the model, an assumption on the schedule of comparative advantage of capital versus labor for the production of tasks, and the estimated elasticities of output per acre, mechanization per acre, and family labor to treatment are enough to measure marginal returns to mechanizable tasks. We estimate the return to mechanizable tasks to be 36% on average per season across farms.

The structural model also allow us to illustrate the channels through which mechanization affects productivity, and to rationalize the nihil effects that we find on output per acre. In the model, a subsidy on capital affects output per farm through three channels: a capital intensification channel, a task intensification channel, a labor replacement channel and a comparative-advantage/productivity channel. The first channel works as in the neoclassical framework: higher capital intensity lowers the marginal product of capital and it 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 is the direct effect of mechanization as a labor saving technology, which raises capital-labor ratios, ceteris paribus. The last channel is the improvement in productivity due to the comparative advantage of capital over labor. In our framework, this productivity effect can be inferred as a residual from the remaining channels and output per farm.

This paper is related to three main literatures.First, to our knowledge, this is the first experimental evidence of the impact of mechanization on the labor market, and on how mechanization interacts with labor market frictions. We document a labor replacement effect consistent with the capital-labor substitution that has been widely emphasized by the literature on automation, (Acemoglu and Restrepo (2019) and papers there cited). Distinctively, our results suggest output standardization in response to mechanization. This standardization is valuable in environments with moral hazard problems, where family labor needs to be allocated to worker supervision, Bharadwaj (2015); Foster and Rosenzweig (2017).[3] Our findings are tightly related to theories of the disparities in average firm size between poor and rich countries based on differences in managerial capabilities and contracting frictions, including Bloom and Van Reenen (2010) and Akcigit et al. (2020). Importantly, we highlight how mechanization of tasks is a valuable mechanism for farmers to pull-back supervision efforts.

Second, 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

[3] 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.

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 purchases, facilitating the use of large, expensive equipment. Methodologically, we show why in an environment where capital-deepening affects total factor productivity endogenously, the randomized variation is not enough to identify returns. We also show how a simple structural model (and the restrictions associated to it) are enough to identify the parameters of interest.[4]

Finally, we relate 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.[5]

[4]The challenges to estimating marginal returns to mechanization are similar to the identification problems for the estimation of a production function. While our computations are fully parametric, we do exploit the restrictions imposed the agents' optimal input choices, as suggested by Gandhi et al. (2020).

[5]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 Setting and Experimental Design

The experiment is a two-stage randomized controlled trial in 190 villages across eight districts in Karnataka.[6] 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 using rental records from our implementation partner (discussed in detail in Section 3) 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

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

were assigned to the control group, and 13 farmers to treatment. Out of the 13 farmers that received the rental price subsidy, 6 farmers received an additional cash grant of equivalent amount. 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 the household 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 take-up, we use it 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.

Due to fieldwork restrictions to minimize the risk of Covid-19 spread, the endline survey was only completed for about 5500 households. Prior to this, we had universal compliance in participation in the endline. We correct for this in several ways. First, 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. Second, we estimate the inverse probability of being surveyed on household characteristics (such land size,pre-intervention participation in the implementation partner's platform, baseline mechanization and household size, area cultivated, and demographic characteristics of the household head) interacted with the treatment dummy variables, and weight all our final estimates with the inverse probability weights (unweighted estimates are nearly identical to the weighted estimates).

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 village-level fixed effect, which we include after showing that the intervention does not have spill-over effects in take-up of mechanization. β identifies the impact 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 presents 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.[7] 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 about 0.8 to one 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 B3 presents results separately for spillover farmers i.e. farmers who did not receive either treatment but were in treated villages. In this regression, farmers in control villages are the omitted group. The probability they rent from the CHC rental market is less than

[7] Less than 5% of the households report a non-unique phone number, a behavior that is not correlated with treatment status. Alternative measures, that use phone number as well as name matching, yield identical treatment effects.

one-tenth the direct treatment effect, indicating that spillover effects were extremely small. Given this, we follow our pre-analysis plan and pool all control farmers for all analysis, and include village-fixed effects in the estimation.

Table 1: Take-Up

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.310****	0.338****	0.307****	0.335****
	(19.00)	(18.66)	(16.98)	(16.53)
1(Cash and Mechanization)		-0.0569****		-0.0576****
		(-3.60)		(-3.47)
Endline Survey			X	X
Observations	7202	7161	5530	5492

t statistics in parentheses. Clustering at the village-level.

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

4.1.2 Overall Mechanization Rental

To understand whether rental vouchers increase participation in the CHC rental market by merely substituting mechanization rental from other providers or if they increase overall 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 (IHS) to dampen the effect of outliers.[8] We similarly standardize the mechanization index to allow us to interpret the effect of treatment in terms

[8]The log function has a similar function, but the IHS allows for negative values.

Table 2: Take-Up by Area

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.285****	0.295****	0.284****	0.296****
	(13.79)	(11.83)	(12.44)	(10.60)
1(Mechanization) X Baseline Area (Acres)	0.00858**	0.0140**	0.00808*	0.0129**
	(1.98)	(2.50)	(1.71)	(2.14)
Baseline Area (Acres)	0.00262**	0.00263**	0.00171	0.00172
	(2.47)	(2.48)	(1.36)	(1.36)
1(Cash and Mechanization)		-0.0237		-0.0245
		(-0.83)		(-0.78)
1(Cash and Mechanization) X Baseline Area (Acres)		-0.0110		-0.0106
		(-1.57)		(-1.34)
Endline Survey			X	X
Observations	6969	6969	5349	5349

t statistics in parentheses

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

of standard deviations of the dependent variable.

Results are presented in Table 3. The offer of a rental voucher increases mechanization by about 0.13 standard deviations (TOT of about 0.36 standard deviations). The effect sizes are relatively modest, but imply that the voucher treatment increased overall mechanization use. Table 4 shows that 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(Mech Index)		
1(Mechanization)	0.140****	0.130***	0.123****	0.116***
	(3.91)	(2.96)	(3.52)	(2.68)
1(Cash and Mechanization)		0.0216		0.0155
		(0.53)		(0.38)
Observations	5349	5349	5349	5349
Baseline Conntrols			X	X

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4: Mechanization Index Treatment Effects

	(1)	(2)	(3)	(4)
		IHS(Mech Index)		
1(Mechanization)	0.0981	0.0821	0.0873	0.0821
	(1.50)	(1.01)	(1.38)	(1.01)
Baseline Area (Acres)	0.0604****	0.0604****	0.0553****	0.0604****
	(6.57)	(6.56)	(6.39)	(6.56)
1(Mechanization) X Baseline Area (Acres)	0.00325	0.00481	0.00323	0.00481
	(0.25)	(0.31)	(0.26)	(0.31)
1(Cash and Mechanization) X Baseline Area (Acres)		-0.00328		-0.00328
		(-0.24)		(-0.24)
1(Cash and Mechanization)		0.0347		0.0347
		(0.46)		(0.46)
Observations	5349	5349	5349	5349

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.2 Labor

As discussed in section 1, a primary impact of mechanization on agriculture is 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 5 and B11. Family male labor declines by 6.5 percentage points and family female labor by 4 percentage points. In contrast, hired labor increases by about 8.5 percentage points for men and about 3.5 percentage points for women. Cash transfers have no marginal effect over and above mechanization. Female labor, both family and hired labor, declines by between 7 to 8 percentage points.

While the elasticities of different types of labor are similar– about 6 to 8 percentage points– they imply quite different impacts on labor use. Mechanization reduces male family labor use by about 0.13 workers per acre over the season, whereas for hired male workers, the impact is much larger, about 0.425 workers per acre. The impact on family female workers is the smallest, about 0.08 workers per acre, and the impact on hired female workers is about 0.52 workers per acre.

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 broad measure of task specialization, in that even if a type of labor engages in a particular task for a small portion of time, that task would be included among its tasks description. Table B12 presents a more narrow 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 that illustrates the role of family size, which provides labor with low or no moral hazard problems, for hired labor (e.g. Bharadwaj, 2015). These moral hazard problems induce task specialization by type of labor.

How does the labor effect impact the span of control on the farm? Since family males are the most likely members of the households engaging in managerial tasks, like supervision, we construct a measure of the span of control as the number of hired workers per family male worker.[9] Table 8 shows that the span of control increases in response to treatment. The effect of mechanization on the span-of-control operates through two channels. First, any labor-saving technology would reduce the ratio of hired labor to family labor, if family labor is held fixed. This yields a decline in the span-of-control given our measurement. Second, if lower labor demand for mechanizable tasks also induces a decline in family labor by for example, reducing the incidence of moral hazard problems, the span-of-control may increase. In our experiment, this second effect, which we associated to output standardization, overturns the labor-saving effect.

We further investigate the role of supervision using detailed data on tasks undertaken and labor supply for four members of the household most involved in agriculture. For each such person, we ask them which tasks they engaged in for the same 15 tasks listed in Table 7, as well as the number of days they worked on the family farm. From these, we construct total days per acre at the household-level for members who report supervising as one of the tasks they do, and for members who do not report supervising. Results are presented in Table 9 –the effects are negative and statistically significant for members that reported supervision, with no effect for members that did not.

Tables B6 to B10 present results for labor used for acre separately for each stage of the production process – land preparation, planting, plant protection, harvesting, and harvest

[9] These are similar to measures of span of control in the prior literature e.g. Bloom et al. (2014).

processing.

Table 6 presents results for mean wages for hired labor by gender across the season (family labor is unpaid) – we do not find any statistically significant impacts of either cash or mechanization on wages.

Table 5: Types of Labor: Treatment Effects

	(1) Ln(Family Males)	(2) Ln(Family Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	-0.00179	-0.0138	0.0234	0.0414
	(-0.08)	(-0.54)	(0.65)	(1.20)
1(Mechanization)	-0.0654***	-0.0701****	-0.0893***	-0.0827***
	(-3.30)	(-3.42)	(-2.90)	(-2.86)
Observations	4426	4435	4408	4409

t statistics in parentheses

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

Table 6: Log Wages: Treatment Effects

	(1) Male Wage	(2) Female Wage	(3) Male Wage	(4) Female Wage
Mechanization	0.0417	0.0104	0.0388	-0.00840
	(1.12)	(0.35)	(0.90)	(-0.22)
1(Cash and Mechanization)			0.00616	0.0404
			(0.10)	(0.92)
Observations	4064	4124	4064	4124

t statistics in parentheses

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

Table 7: Tasks Ever Performed by Types of Labor

Sno.	Task	Family Male	Hired Male	Family Female	Hired Female
1	Supervision of farm labor	87.87	3.13	30.75	1.28
2	Sourcing inputs	72.73	18.45	17.09	7.78
3	Land preparation	78.00	58.56	30.65	20.14
4	Manure application	72.74	62.60	38.18	32.36
5	Sowing seed	61.62	54.21	50.11	49.58
6	Transplanting	44.73	38.70	57.38	64.73
7	Chemical Fertilizer Application	61.66	51.81	34.62	30.52
8	Hand Weeding	48.05	34.53	67.67	72.98
9	Interculture	62.64	44.46	44.44	41.37
10	Plant protection	54.62	37.51	31.28	26.16
11	Irrigation	47.31	23.61	16.93	12.00
12	Tending to Land	67.80	22.53	34.08	13.63
13	Harvesting	62.78	58.54	52.62	59.42
14	Threshing	51.30	43.56	38.74	40.04
15	Marketing	54.87	5.05	6.68	2.53

Table 8: Span of Control: Treatment Effects

	(1) All Hired/Male Family	(2) Male Hired/Male Family	(3) Female Hired/Male Family
1(Cash and Mechanization)	-0.556	-0.257	-0.264
	(-1.23)	(-1.41)	(-0.86)
1(Mechanization)	0.663*	0.338*	0.298
	(1.69)	(1.78)	(1.09)
Observations	4124	4124	4132

t statistics in parentheses

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

Table 9: Intra-Household Labor: Treatment Effects During Harvest

	(1)	(2)	(3)	(4)
	Log(Days Per Acre)			
	Supervising HH Members		Non- Supervising HH Members	
1(Mechanization)	-0.185****	-0.239****	-0.0592	-0.00512
	(-5.43)	(-5.84)	(-1.16)	(-0.09)
1(Cash and Mechanization)		0.120**		-0.118*
		(2.25)		(-1.71)
Observations	5302	5302	5299	5299

t statistics in parentheses

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

4.3 Productivity

In this section, we show treatment effect estimates on productivity. Cash has the ability to relax liquidity constraints, and may crowd in input intensification and increase productivity. We measure productivity as 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.[10] We also estimate the impacts of both revenue and profit per worker. Results per acre are presented in Tables 12 and 13– the latter present heterogenous effects by area. Results per worker are presented in Tables 10 and 11. We find that neither treatment impacts productivity per worker on average.

Table 10: Productivity Per Worker: Treatment Effects

	(1) Log(Rev/Worker)	(2) IHS(Profit/Worker)	(3) Log(Rev/Worker)	(4) IHS(Profit/Worker)
1(Mechanization)	0.134**	0.180	0.0899	0.0580
	(2.58)	(1.21)	(1.62)	(0.32)
1(Cash and Mechanization)			0.0950	0.265
			(1.29)	(1.35)
Observations	4522	5244	4522	5244

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 14 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 find that mech-

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

Table 11: Productivity Per Worker: Treatment Effects

	(1) Log(Rev/Worker)	(2) IHS(Profit/Worker)	(3) Log(Rev/Worker)	(4) IHS(Profit/Worker)
1(Mechanization)	-0.0329	-0.218	-0.108	-0.437
	(-0.33)	(-0.97)	(-1.02)	(-1.60)
Baseline Area (Acres)	0.0987****	0.212****	0.0987****	0.212****
	(5.12)	(4.98)	(5.12)	(4.98)
1(Mechanization) X Baseline Area (Acres)	0.0333	0.0873	0.0426	0.109
	(1.19)	(1.41)	(1.37)	(1.52)
1(Cash and Mechanization) X Baseline Area (Acres)			-0.0202	-0.0463
			(-0.53)	(-0.60)
1(Cash and Mechanization)			0.163	0.471
			(1.07)	(1.37)
Observations	4457	5163	4457	5163

t statistics in parentheses

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

Table 12: Productivity Per Acre: Treatment Effects

	(1) Log(Rev/Acre)	(2) IHS(Profit/Acre)	(3) Log(Rev/Acre)	(4) IHS(Profit/Acre)
1(Mechanization)	0.00373	0.151	-0.0530	-0.0822
	(0.07)	(0.73)	(-0.85)	(-0.33)
1(Cash and Mechanization)			0.122	0.509*
			(1.38)	(1.80)
Observations	4563	5349	4563	5349

t statistics in parentheses

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

Table 13: Productivity Per Acre: Treatment Effects

	(1) Log(Rev/Acre)	(2) IHS(Profit/Acre)	(3) Log(Rev/Acre)	(4) IHS(Profit/Acre)
1(Mechanization)	0.0772	-0.322	-0.00260	-0.674*
	(0.76)	(-1.00)	(-0.02)	(-1.69)
Baseline Area (Acres)	-0.0831****	0.203****	-0.0831****	0.203****
	(-4.63)	(3.66)	(-4.63)	(3.66)
1(Mechanization) X Baseline Area (Acres)	-0.00823	0.113	0.000203	0.144
	(-0.29)	(1.38)	(0.01)	(1.47)
1(Cash and Mechanization) X Baseline Area (Acres)			-0.0182	-0.0631
			(-0.43)	(-0.58)
1(Cash and Mechanization)			0.172	0.758
			(1.00)	(1.49)
Observations	4497	5266	4497	5266

t statistics in parentheses

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

anization reduces raw material expenditure, with no marginal impact of cash. We do not find any statistically significant impact on hired labor, though the negative point estimate is consistent with the effects on labor use.

Table 14: Input Expenditure Treatment Effects

	(1) Log(Raw Materials Expenditure/Acre)	(2)	(3) Log(Hired Labor Expenditure/Acre)	(4)
1(Mechanization)	-0.132***	-0.135***	-0.0525	-0.0552
	(-3.20)	(-2.83)	(-0.79)	(-0.72)
1(Cash and Mechanization)		0.00619		0.00583
		(0.11)		(0.07)
Observations	4611	4611	4352	4352

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 15 presents the results. While there is no difference in the binary probability for whether a household reports income from non-agricultural sources, non-agricultural income increases, and the effect is statistically and economically significant – a point estimate of 40%– if changes in non-agricultural income are considered.

Table 15: Household-Level Non-Agricultural Income: Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Any Non-Agri Income)		Log(Non-Agri Income)		Change Log(Non-Agri Income	
1(Mechanization)	0.0153	0.0172	0.138	0.162	0.414**	0.460**
	(1.16)	(1.16)	(1.11)	(1.15)	(2.40)	(2.27)
1(Cash and Mechanization)		-0.00427		-0.0540		-0.103
		(-0.26)		(-0.36)		(-0.47)
Observations	5349	5349	5349	5349	5349	5349

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 interpret the channels through which we observe the treatment effects from the experiment. 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.

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 needs to be supervised for workers to be productive. The timing of processes matters insofar the productivity of workers at the harvesting stage depends on how the preparation stage took place. We assume that when tasks are mechanized at preparation, this yields a proportional increase in the productivity of workers at harvest.[11]

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.

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.

Let the size of a plot be l, capital services k, hired labor, n_s and family labor n_f. Hired labor must be supervised and the marginal product of labor is increasing in family (effort). 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

[11] Alternatively, we could have assumed that output from the preparation stage is an input into the harvesting stage.

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

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

where $\alpha_l = 1 - \alpha - \alpha_f$ 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 they hold a minimal scale $\bar{l}$. This feature is consistent with the observed higher mechanization for larger plot holders at baseline. We assume constant returns to scale in tasks, family and land but because land is assumed a fixed factor, the profits of farming are indeed the returns to land.[12] 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.[13]

$$y^H = b_s(I)n_f^{\alpha_f} n_s^{\alpha} l^{\alpha_l}.$$

where $\alpha + \alpha_f + \alpha_l = 1$ and that mechanization at the preparation stage has direct impact on the productivity of workers at the harvesting stage.

[12] If we assume that family labor is not paid market wages, the profits of farming are the returns to land and family labor.

[13] Our survey suggest that mechanization practices are almost exclusively allocated to land preparation.

Assumption 2 $b_s(I)$ 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 services,

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

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

where $p(i)$ is the price of output for task i. It is straightforward to show that there exist a threshold I such that all tasks with indexes $i < I$ will be mechanized, while all tasks with indexes $i > I$ will be completed with supervised labor.

The optimality conditions across tasks require

$$\alpha y^P = p(i)x_i \qquad (x_i)$$

An implication of these conditions is that the quantities of labor and capital in each task are proportional to each other. It also 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

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

where $A^P = \bar{a}_k(I)\bar{a}_s(I)$ is an endogenous productivity term, where $\bar{a}_k(I) \equiv \left(\frac{\prod_{i=0}^{I} a_k(i)}{I^I}\right)^{\alpha}$, $\bar{a}_s(I) \equiv \left(\frac{\prod_{i=1-I}^{1} a_s(i)}{(1-I)^{1-I}}\right)^{\alpha}$. A few features of the technology are worth pointing out. First, the ratio of non-family to family workers is endogenous. Second, whereas there are overall constant returns to factors, the profits from farming equal the return to the fixed factor which we assume it is land, α_l. If in addition we assume that family labor is not properly compensated (for the opportunity cost of their time), the profits from farming include the returns to family labor, α_f. Given the production technology, even if farmers were compensated at market wages, the market return to family labor would be $\alpha_f(1-I)$ and therefore declining in the number of mechanized tasks. In addition, the profits (net of family wages) would be a fraction $\alpha_l + \alpha_f I$, increasing in mechanization.

Given the above technology, we can solve for the optimality conditions for family labor, supervised 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 Standard optimality conditions yield the key predictions for input allocations (see Appendix A), and therefore omitted. Only one feature of the allocation is worth pointing out. A higher share of mechanized tasks at the preparation stage improves productivity at harvesting. Given that land is a fixed factor, absent any movements in output at the preparation stage, the model predicts decline in both family and hired labor.

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 per acre 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,

$$\frac{w_s}{r} = \frac{k}{n_s}\frac{1-I}{I} \tag{3}$$

Then capital-labor ratios are equalized across farms if the level of mechanization are the same (I). The levels (or scales) of operation are different through differences in land size. But larger farms are more mechanized at baseline, implying that the threshold for mechanization is higher, i.e. more tasks are mechanized.

Totally differentiating the above expression we obtain,

$$\frac{dk}{dr} = -\frac{\frac{w_s}{r^2} + \frac{dk}{dr} - \frac{dn_s}{dr} + \frac{d\frac{1-I}{I}}{dr}}{\frac{1-I}{I}\frac{1}{n_s}}$$

Therefore if the elasticity of labor demand to the subsidy is proportional to the elasticity of the threshold to the subsidy, the model predicts no difference in mechanization responses across sizes.[14]

Fact 4.a *Family labor falls at preparation*

A lower cost of capital $r^s < r$ induces mechanization, or a higher threshold I.

At the margin, the output produced by mechanized services or labor should equalize, i.e.

$$\frac{k}{n_f^{\frac{\alpha_f}{\alpha}} n_s} = \frac{a_s(I)}{a_k(I)} \frac{I}{1-I} \tag{4}$$

Therefore, the threshold is solved non-linearly from the above equation. Given Assumption 1 higher capital available implies a higher threshold I. Ceteris paribus, the optimality condition n_f induces lower family labor. The reason is that the marginal product of family labor, $(1-I)\alpha_f \frac{y^p}{n_f}$ falls when the degree of mechanization increases, ceteris paribus.

Fact 4.b *Family labor falls at harvesting* This is a direct consequence of Assumption 2 and the production structure at the preparation stage. If a farm became more mechanized at

[14] In principle, any movement in the threshold and the labor demand that is uncorrelated with size would generate the result. The challenge is that the threshold and therefore, its elasticity, is correlated with size. Such a feature then require proportional changes in employment to offset the correlation with size.

the preparation stage, total factor productivity at the harvesting stage increases. If output did not change at the preparation stage, it is optimal then to lower the flexible input in harvesting which includes family labor.

Fact 5 *Labor hired falls in all processes* This is a direct consequence of the task replacement effect at the preparation stage, and the productivity effect on labor (through output standardization) in all other processes. The task replacement is fully described in equation 3. The marginal product of labor is higher at the harvesting stage, but because wages and output prices do not change, and the output produced is the same as before the price of harvesting output declines, relative to final output, and hired labor declines or remains the same.

Fact 6 *Profitability does not increase on average* Given that land is the fixed factor, profits equal the returns to land. Family labor is also included into the profitability measures whenever their effort is not properly compensated. 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 preparation stage.

From the optimality conditions of the preparation stage we can compute the change in input ratios from a change in the rental price of capital. Therefore, taking logs to the expression for output per acre and totally differentiating we obtain

$$\frac{d\frac{y^P}{l}}{dr}\frac{r}{\frac{y^P}{l}} = \underbrace{\frac{dA^P}{dr}\frac{r}{A^P}}_{productivity} + \underbrace{(\alpha I + (1-I)\alpha_f)\frac{dk}{dr}\frac{r}{k}}_{intensive-mech} -$$

$$\underbrace{(\alpha_f I \ln(k) + \alpha I \ln(\frac{n_f^{\frac{\alpha_f}{\alpha}} n_s}{k}))\frac{dI}{dr}\frac{r}{I}}_{extensive-mech} + \underbrace{(1-I)(\alpha_f+\alpha)\frac{dn_f}{dr}\frac{r}{n_f}}_{labor-replacement} \tag{5}$$

Equation 5 highlights the key channels through which mechanization affects productivity. The first one is the *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 fourth and last one is the *labor replacement effect*. The sign of the extensive mechanization effect is unambiguously negative, i.e. more tasks get mechanized when the cost of capital falls, The sign of the intensive-mechanization effect is unambiguously negative, i.e. farmers mechanize when the cost of capital falls. The sign of the labor-replacement effect is positive, there are less workers in the farm when the cost of capital falls. 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.

The productivity term is a non-monotonic function of the profile of comparative advantage. For relatively low levels of mechanization, additional mechanization improves productivity. In the language of the model, capital has a comparative advantage over labor for low indexes tasks. For relatively high level of mechanization, additional mechanization is detrimental to productivity. In the context of the model, labor has a comparative advantage over capital for high indexes tasks. In addition, the slope of the change in production varies with the shape of the comparative advantage. 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 in response to the rental rate subsidy and productivity improves.

6 Returns to Capital

Armed with the key predictions of the randomized control trial and those of the model economy we are now ready to estimate marginal returns to capital. The production structure of the model yields,

$$\ln y^P = \ln A^P + \alpha I \ln(k) + \alpha(1-I)\ln(n_s) + \alpha_f(1-I)\ln(n_f) + \alpha_l \ln(l)$$

so that the returns to capital as summarized by αI while the returns to mechanizable tasks are summarized by α. There is an extensive literature in industrial organization and development economics describing the challenges of estimating these parameters, i.e. the shape of the production technology. Importantly, reverse causation between the levels of output and capital, as well as the correlation between the residuals (in our case summarized by the endogenous production term, A^P) and the regressors. De Mel et al. (2008) proposed to use the capital randomization as an exogenous variation to identify the parameter of interest. In our set up, the experiment is not a valid instrument (even after controlling for changes in other inputs of production) because the errors are correlated with treatment and therefore violates the exogeneity requirement. To make progress, we rely on insights from the industrial organization literature and exploit the optimality conditions of the structural model to identify the parameter of interest.[15]

6.1 Identifying the mechanization threshold.

We rely on two structural equations of the model to identify the parameters of interest,i.e. the mechanization threshold and the shape of the profile of comparative advantage. The identification follows from the optimality of the mechanization threshold, equation 4, and the

[15] As suggested by Gandhi et al. (2020) for a non-parametric approach to estimating production technologies.

predicted relationship between output and productivity elasticities to treatment, equation 5. We first identify the threshold for mechanization as summarized by I. Then, we back out the return to mechanizable tasks from the optimality conditions of capital and the threshold. To identify the threshold we rely solely on the elasticities induced by the experiment, and an assumption on the shape of the profile of comparative advantage for capital relative to labor. The parameter governing the shape of that profile is then calibrated to match the productivity gains implied by the experimental elasticities.

From the optimality condition for capital we have,

$$\frac{d\ln(\frac{y^p}{l})}{d\ln(r)} = 1 + \frac{d\ln(\frac{k}{l})}{d\ln(r)} - \frac{d\ln(I)}{d\ln(r)} \tag{6}$$

Therefore, the difference between the treatment effects on output per acre and capital per acre identify the change in the mechanization threshold. But the key variable of interest the mechanization threshold itself, I.

Importantly, one can use the inferred change in the threshold and the treatment effect on family to capital ratios to identify this level, conditional on an assumption on the shape of the comparative advantage, $\frac{a_k(i)}{a_s(i)}$. Assume that the functional form for the comparative advantage is a polynomial of the ratio $\frac{I}{1-I}$, which satisfies Assumption 1. For example, $\frac{a_k(i)}{a_s(i)} = \frac{1-I}{I}$ follows the specification of Acemoglu and Zilibotti (2001) for tasks performed by skilled and unskilled workers. Let $g\left(I\right) \equiv \frac{I}{1-I}\frac{a_s(I)}{a_k(I)}$.

Using the solution to the optimal threshold,

$$\frac{d\ln(I)}{d\ln(r)} = -2\frac{d\ln(I)}{d\ln g\left(I\right)}\frac{d\ln(\frac{k}{n_f^{1+\frac{\alpha_f}{\alpha}}})}{d\ln(r)} \tag{7}$$

where we have assumed that the shadow value of hired labor and family labor are proportional to each other, with a factor proportionality that is orthogonal to treatment, i.e. $w_f = w_s\omega$

for ω a constant.[16]

Assumption 3 Let the shape of the comparative advantage satisfy $g(I) \equiv B\left(\frac{I}{1-I}\right)^{\beta}$ for $\beta > 1$.

Then, the elasticity of the function g to the movement in the threshold I is a linear function of it, and independent of the shifter B.

$$\frac{d\ln g(I)}{d\ln(I)} = -\frac{\beta}{1-I}$$

Combining equations 7 and 6 we obtain the identification restriction for the level of the threshold,

$$1 + \frac{d\ln(\frac{k}{l})}{d\ln(r)} - \frac{d\ln(\frac{y^p}{l})}{d\ln(r)} = 2\frac{\beta}{1-I}\left[\frac{d\ln(k)}{d\ln(r)} - (1+\frac{\alpha_f}{\alpha})\frac{d\ln(n_f)}{d\ln(r)}\right] \tag{8}$$

All the elasticities in the above expression are directly estimated from the experiment as a function of the factor shares of mechanizable tasks and family labor, α, α_f. If one assumes $\alpha = \alpha_f$ the above restriction is sufficient to solve for the threshold. If this is not the case, we need a system of restrictions to fully identify the relevant parameters of the model. We describe the additional restrictions below.

The capital share for the control group satisfies,

$$\frac{rk}{y^p} = \alpha I \tag{9}$$

and therefore identifies α conditional on the threshold.

The assumption on the production function implies that we can identify then $\alpha_f = \frac{\pi}{y^p} - \alpha_l$.

[16] Appendix B shows that this indeed the case when worker's effort is not contractible and family labor supervises hired workers to avoid shrinking.

Combining equations 9 and the assumption of constant returns, we

$$\frac{\alpha_f}{\alpha} = (\frac{\pi}{y^p} - \alpha_l)\frac{I}{\frac{rk}{y^p}}$$

, where α_l can be imputed from the usercost of land.

Replacing the above equation into the main identification restriction 8 we obtain a non-linear restriction on the threshold which we use for identification.

Before describing the parameterization of the model let us briefly discuss how the structural features of the model allow us to pin down family wages, which are intrinsically unobserved. Using the optimality conditions for labor and the expenditure share for hired labor we can infer family wages from the following identity

$$\frac{\alpha}{\alpha_f} = \frac{w_s n_s}{w_f n_f},$$

After computing the return to mechanizable tasks, α all variables are observable except for w_f. We discuss their estimation and how they compare to market wages in Section 6.5. We also discuss how the difference between market wages and the shadow value of family labor relate to the incidence of contracting frictions through the lens of a simple principal-agent problem with unobserved effort.

6.2 Parameterization

In this section we infer the threshold for mechanization for the median farmer in our sample, and for those cultivating 4 acres or more. Table 16 describes the parameterization of the model. Farm revenue and expenses are computed for the median farm in the control group. Revenues are net of intermediate input expenses because we only modelled value-added. The elasticities of revenue per acre, capital per acre and family labor are as reported in Section

Table 16: Parameterization

Levels (Baseline)		Benchmark	Large ($>$ 4 acres)	Source
	$\frac{y}{l}$	17300	14740	Control
	$w_s n_s$	11188	6450	Control
	rk	3000	1667	Control
Elasticities				
	$\epsilon_{\frac{y}{l}}$	-0.053	-0.002	Table 12 & Table 13
	$\epsilon_{\frac{k}{l}}$	0.130	0.101	Table 3 & Table 4
	$\epsilon_{\frac{n_f}{l}}$	-0.065	-0.002	Table 5 & Table B11
Others				
	β	1.9		calibrated to target ϵ_{A^p}
	$\epsilon_{r,treatment}$	1		experimental design

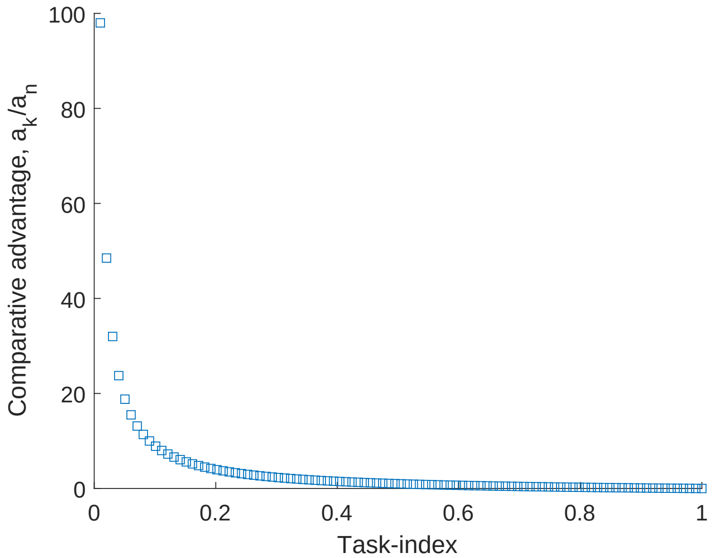
Column (1) presents the benchmark parameterization, where revenue and expenses are computed as the median in the sample and the elasticity are the main elasticities discussed in Section 4. Column (2) presents the parameterization for large farmers, i.e. with a cultivated area of 4 acres or more. Column (3) presents the sources for the parameterization. The elasticity of the function describing the comparative advantage is calibrated indirectly to match the implied changes in total factor productivity from the experiment.

4. Importantly, the shape of the comparative advantage is calibrated to match the implied elasticity of total factor productivity to the subsidy, $\beta = 1.9$, see figure 1.[17] At the same time we impose an elasticity of the cost of capital to treatment of 1. The reason is that vouchers were calibrated to subsidize the median usage of equipment observed in prior seasons.

Interestingly, larger farmers reports lower revenues and lower expenses in all inputs, which indicates lower utilization and possibly lower productivity. These differences expenses are reflected in factor shares. To identify mechanization thresholds, we need to construct an estimate of the land share in production, α_l. To do that, we compute the user cost of capital using a standard euler equation for a durable good. The key ingredients for such an exercise are an estimate for the real interest rate, which we assume at 4% per year; a depreciation

[17] When we alternatively use the specification in Acemoglu and Zilibotti (2001), $\beta = 2$, we find that productivity should have increased more in response to treatment than what we find through the experiment.

Figure 1: Calibrated profile of comparative advantage



This figure plots the calibrated profile for comparative advantage of capital over labor in mechanizable tasks, $\frac{a_k(i)}{a_n(i)}$.

rate for land, which we set at 2% per year; an estimate for the price of land, which we set at ₹240000 per acre, consistent with the estimates in Chakravorty (2013); and an expectation for its real price appreciation, which we set at 6% per year. This yields a user cost per acre of ₹288 per year.[18] The share of family labor is computed as a residual from the share of capital, labor and land, and the assumption of constant returns. Table 17 presents these results.

6.3 Returns to mechanizable tasks

At the median, the share of capital is 17% while the share of hired labor reaches 65%. The return to land is estimated at 3% and the remaining 15% is assigned to the family labor. With this parameterization, we find that 49% of all mechanizable tasks are indeed performed

[18]We run robustness checks over these estimates of the user cost of land in the discussion section.

Table 17: Returns

Benchmark, median 2 acres.					
αI	$\alpha(1-I)$	α_l	α_f	I	α
0.17	0.65	0.03	0.15	0.482	0.36
Large, > 4 acres.					
αI	$\alpha(1-I)$	α_l	α_f	I	α
0.11	0.44	0.08	0.37	0.768	0.15

This table presents estimates of the inputs shares for different factors of production, as well as the identified threshold for mechanization I and the returns to mechanizable tasks, α.

by capital. This threshold implies a return to mechanizable tasks of 36%, our main estimate.

Given the potential disparities in returns across sizes, we also run our threshold identification exercise for relatively large farmers, with cultivated areas of more than 4 acres. Consistent with the lower than median expenses in capital we find a capital expenditure share of 11% (vs. 17% in the benchmark). However, given the elasticities uncovered by the experiment, we find that these farmers are relatively more mechanized, with a share of mechanized tasks of 77% (vs. 49% at benchmark). The return to mechanizable tasks for relatively large farmers is less than half of the median, at 15%.

Discussion. In theory, our estimates could be sensitive to the computation of the returns to land, and through it, of the return to family labor, α_f. Quantitatively they are not. If we assume no return to family labor, i.e. all profits are considered land returns, the threshold of mechanizable tasks increases to 54% (from 48% at benchmark) and the return to mechanizable tasks falls to $\alpha = 32\%$ (from 36% at the benchmark).

A key restriction to the identification of the threshold of mechanizable tasks as well as the capital share of output is the assumption that farmers behave optimally and in a frictionless capital market when choosing mechanization. Suppose that these rentals markets were to function on credit and that farmers are heterogeneously impacted by credit constraints. These constraints would generate a wedge between the marginal product of capital and its market price.[19] If farmers would like to obtain more capital but can not, the value of the marginal product of capital would be above its market price. Let us model this gap as $\tau \in (0,1)$ that satisfies,

$$\frac{rk}{y^p} = \alpha I \tau \tag{10}$$

Hence, as $\tau \rightarrow 1$ the marginal product lines up with the market price, and as $\tau \rightarrow 0$ the marginal product of capital goes to infinity (and the capital demand declines).

This wedge could have implications for the computation of the marginal return to mechanizable tasks through their effect on the share of tasks being mechanized. Quantitatively however, this channel is not strong. When we include a gap between the market rental rate and the value of the marginal product of capital of 90% we find that the mechanization threshold shifts to 54% (from 49% at benchmark) and that the return to mechanizable tasks (given the wedge), $\alpha\tau$, is now 33% instead of 36%. The reason for these small quantitative effects is that the wedge only affects the threshold for mechanization by mediating shifts in family labor. Quantitatively, these shifts are small relative to the changes in mechanization hours. Importantly, if we would be able to disentangle the wedge from those returns, we would conclude that the return to capital is $\alpha = 37\%$, 1pp higher than our benchmark.

6.4 Effects on productivity

One of the predictions of our experiment is that revenue per acre (and profitability) increases in response to the subsidy in capital but not significantly. In this section we explore the channels affecting total factor productivity, which is endogenous in our set up. In particular, we parameterize equation 5 using the estimates of the elasticities, the identified threshold and baseline expenses.[20] To compute the size of different channels we also need measures of

[19]Notice that we are balanced in terms of our index of credit constraints and therefore, the estimates of the elasticities are robust to differences in these constraints.

[20]Recall that the shape of the comparative advantage (as summarized in β) is calibrated indirectly to match the productivity effect for the median farmer.

Table 18: Productivity Decomposition, channels

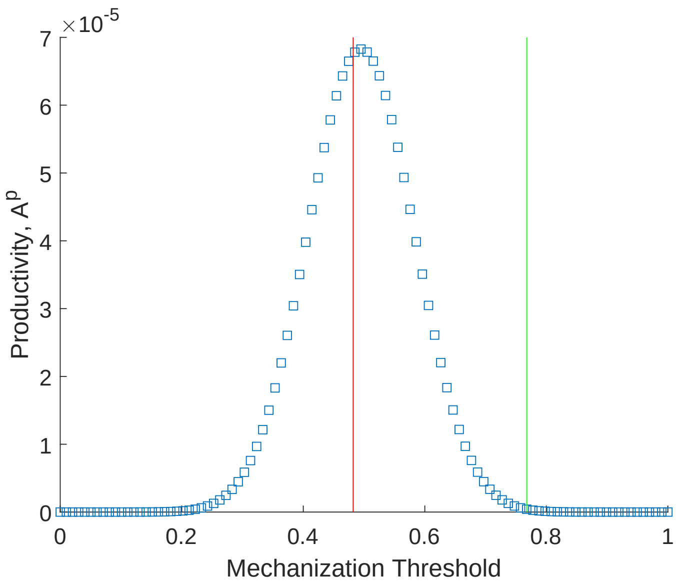
Revenue per acre	Intensive mechanization	Extensive mechanization	Labor Replacement	Total	TFP
(1)	(2)	(3)	(4)	(5) -(2)+(3)-(4)	(6) (5)+(1)
-0.05	0.032	0.068	-0.05	0.09	0.03

Each element of the table computes different channels through which a subsidy on mechanization affects revenue per acre, as characterized in equation 5. The elasticities to treatment and median expenses for the control group are as described in Table 16, input shares are reported in Table 17. The elasticity of total factor productivity is computed as a residual of the elasticity of revenue per worker, and all channels.

average mechanization, i.e. hours per acre for the control (which we estimate at 4 hours per acre at the median), and family labor per acre for the control, number of workers (which we estimate at 3.3 workers). Table 18 reports the relative strength of each channel for the changes in revenue per worker. In addition to the direct effects of capital which we highlight in equation 5, we also report the impact through changes in labor demand.

If we abstract from the effect of treatment on other inputs' demand, we find that the intensive mechanization (more capital) effect is stronger than the extensive mechanization effect (more tasks performed by capital). The labor replacement channel has the same magnitude as the elasticity of revenue per acre. Hence, changes in productivity are accounted for the difference between the intensive and the extensive mechanization channels. These quantitative effects indicate that most of the revenue per acre effects are accounted for the task-productivity effect. In all, we find that the elasticity of total factor productivity to treatment is 3pp, 8 pp higher that the effect on revenue per worker (at -5pp), for a visual representation see figure 2.

Figure 2: Calibrated profile of comparative advantage



This figure plots implied productivity for different levels of the mechanization threshold in blue. In red we plot the mechanization threshold for the median farmer. In green we plot the mechanization threshold for large scale farmers.

6.5 Family compensation and contracting frictions.

As we mention towards the end of Section 6.1, once the mechanization threshold is identified, it is possible to back-up family wages from the optimality conditions for labor.

$$w_f = \frac{w_s n_s}{n_f} \frac{\alpha_f}{\alpha},$$

Using the median average farming household size of 3.3 adults we find implied wages per season per household member of ₹606, below the average observed wages for hired workers, ₹815 per worker per season. The pull-back of family labor in response to mechanization is then consistent with the gap between family and market wages, as well as with contracting frictions that tie family workers to their farm. Appendix B makes this statement formally.

7 Conclusion

We provide the first available measures of the returns to mechanization from experimental evidence. We find no statistically significant increases in productivity on average, but we do find declines in hired and family labor in the farm. We structurally estimate the returns to mechanizable tasks at 35%. 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 we will include policy counterfactuals exploiting the calibrated structural model and census information collected during our experiment.

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A Allocations

Processing stage The optimality conditions with respect to input intake are

$$\alpha_h \frac{y^P}{n_h} = w \tag{n_h}$$

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

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

$$\alpha I \frac{y^P}{k} = r \tag{k}$$

Harvesting stage The optimality conditions with respect to input intake are

$$\alpha_f \frac{y^H}{n_f} = w_f \tag{n_f^H}$$

$$\alpha \frac{y^H}{n_s} = w_s \tag{n_s^H}$$

B Allocations

Assume workers effort in the field is not observable, and that worker can provide effort or shirk. If she shirks, the worker gets a benefit of proportional to their wage, ωw_s. Therefore, ω is a measure of the incidence of the frictions, i.e. the incentives to the worker not to exert effort. Family workers can supervise workers, in which case they can catch a shrinking worker with probability $\min \frac{n_f}{n_s}, 1$. We assume that the probability of catching a shirking worker declines with the number of workers supervised by each family labor. Then, a standard incentive compatibility constraint implies that the worker does not shirk iff the wage she gets is weakly higher than the expected return from shirking,

$$w_s \geq \omega w_s + \left(1 - \frac{n_f}{n_s}\right) w_s,$$

assuming, $\frac{n_f}{n_s} \leq 1$. If the worker shirks, it is as if the worker did not work in the farm (no hours are allocated to production). The optimal supervision effort for the family is

$$\frac{n_f}{n_s} = \omega$$

From the optimality conditions in farming, an interior solution for family labor and hired labor must satisfy

$$\frac{n_f}{n_s} = \frac{\alpha_f}{\alpha} \frac{w_s}{w_f}$$

Hence, combining these two conditions, the difference in wage between family and hired workers (after adjusting for factor shares) is a measure of the incidence of the contracting friction, ω. The lower family wages relative to market wages the higher ω, and therefore the higher the incentives to shirk. Given our estimates of market wages over the season, ₹815, family wages, ₹606, and factor shares, α, α_f, we find that incentives for shirking about for about a quarter of market wages, $\omega = 0.24$.

C 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	$\geq$ 4 acres	3500	0
2	$\geq$ 4 acres	3500	1750
1	$\geq$ 4 acres	1750	0
1	$\geq$ 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	$\geq$ 4 acres	3500	0
1	$\geq$ 4 acres	3500	1750
1	$\geq$ 4 acres	1750	0
1	$\geq$ 4 acres	1750	1750

All treatment and control villages have 20 control farmers each.

Table B2: Balance Table

	(1)
Area Cultivated	0.0703
	(0.62)
1(Matched to Platform)	0.000240
	(0.02)
IHS(Mechanization Index)	0.0126
	(0.48)
Household Size	-0.0140
	(-0.25)
1(Credit Constrained)	0.00986
	(1.30)
1(Household Head is Male)	-0.0116
	(-1.21)
1(SC/ST Household)	-0.00141
	(-0.09)
Log (Male Wage)	-0.00620
	(-0.21)
Log (Female Wage)	0.0195
	(0.82)
Log(Nonagricultural Income)	-0.00642
	(-0.05)
Log(Revenue per acre)	-0.0758
	(-0.58)
Number of Family Males Working on the Farm	0.0339*
	(1.73)
Number of Family Females Working on the Farm	-0.00560
	(-0.32)
Number of Hired Males Working on the Farm	0.335
	(1.37)
Number of Hired Females Working on the Farm	-0.00560
	(-0.32)
Log (Span of Control: All Hired Workers to Male Family Workers)	0.0224
	(0.68)
Number of Specialized Tasks: Family Males	-0.0371
	(-0.65)
Number of Specialized Tasks: Hired Males	0.0567*
	(1.71)
Number of Specialized Tasks: Family Female	-0.0144
	(-0.72)
Number of Specialized Tasks: Hired Female	0.0257
	(0.83)
1(Own Any Equipment)	0.0176
	(1.02)
Joint F-Stat	**0.47**
Observations	7235

t statistics in parentheses

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

Table B3: Take-Up: Direct and Spillover Effects

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.324****	0.353****	0.329****	0.357****
	(16.71)	(16.99)	(16.00)	(16.03)
1(Spillover)	0.0250	0.0250	0.0266*	0.0266*
	(1.57)	(1.57)	(1.77)	(1.76)
1(Cash and Mechanization)		-0.0614****		-0.0596****
		(-3.90)		(-3.49)
EL Survey			X	X
Observations	7202	7161	5530	5492

t statistics in parentheses. Clustering is at the village-level.

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

Table B4: Take-Up Up to Four Months Post-Intervention

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.00965***	0.00916**	0.00707*	0.00685
	(3.07)	(2.47)	(1.93)	(1.48)
1(Cash and Mechanization)		0.00156		0.00100
		(0.33)		(0.20)
EL Survey			X	X
Observations	7202	7161	5530	5492

t statistics in parentheses. Clustering is at the village-level.

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

Table B5: Mechanization Index Treatment Effects by Stages of Production

	(1) Land Preparation	(2) Planting	(3) Harvesting
1(Cash and Mechanization)	0.0205	-0.0104	0.00653
	(0.54)	(-1.20)	(0.59)
1(Mechanization)	0.0881**	0.0162	0.0253*
	(2.32)	(1.41)	(1.77)
Observations	5331	5227	5271

t statistics in parentheses

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

Table B6: Types of Labor: Treatment Effects During Land Preparation

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	0.00196	-0.000710	-0.0183	-0.0213*
	(0.21)	(-0.07)	(-0.78)	(-1.82)
1(Mechanization)	-0.0324****	-0.0148*	-0.0233	-0.00524
	(-3.48)	(-1.74)	(-1.18)	(-0.41)
Observations	4426	4435	4407	4400

t statistics in parentheses

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

Table B7: Types of Labor: Treatment Effects During Planting

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	-0.0134	-0.00925	0.00260	0.0612**
	(-1.33)	(-0.72)	(0.11)	(2.17)
1(Mechanization)	-0.0198**	-0.0300***	-0.0461**	-0.0737****
	(-2.03)	(-2.88)	(-2.21)	(-3.41)
Observations	4429	4443	4419	4422

t statistics in parentheses

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

Table B8: Types of Labor: Treatment Effects During Plant Protection

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	-0.00935	-0.0158	-0.00948	0.00914
	(-1.00)	(-1.37)	(-0.38)	(0.36)
1(Mechanization)	-0.0229**	-0.0154	-0.0440*	-0.0265
	(-2.35)	(-1.56)	(-1.91)	(-1.07)
Observations	4426	4444	4412	4401

t statistics in parentheses

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

Table B9: Types of Labor: Treatment Effects During Harvest

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	0.00358	-0.0106	0.0158	0.00607
	(0.34)	(-0.81)	(0.56)	(0.19)
1(Mechanization)	-0.0251**	-0.0176*	-0.0522*	-0.0254
	(-2.38)	(-1.76)	(-1.95)	(-0.89)
Observations	4430	4443	4414	4405

t statistics in parentheses

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

Table B10: Types of Labor: Treatment Effects During Harvest Processing

	(1) Ln(Family Males)	(2) Ln(Famiy Females)	(3) Ln(Hired Males)	(4) Ln(Hired Females)
1(Cash and Mechanization)	0.000659	-0.00121	0.0193	0.0363
	(0.06)	(-0.11)	(0.77)	(1.40)
1(Mechanization)	-0.0276***	-0.0300****	-0.0610***	-0.0475**
	(-2.62)	(-3.40)	(-2.86)	(-2.34)
Observations	4434	4435	4415	4404

t statistics in parentheses

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

Table B11: Types of Labor: Treatment Effects by Area

	(1) Ln(Family Males)	(2) Ln(Family Males)	(3) Ln(Famiy Females)	(4) Ln(Hired Males)	(5) Ln(Hired Females)
1(Mechanization)	-0.0176	-0.0176	0.0451	0.0857	0.0866
	(-0.47)	(-0.47)	(1.12)	(1.51)	(1.46)
1(Cash and Mechanization)	0.0252	0.0252	-0.0388	0.0600	0.125*
	(0.55)	(0.55)	(-0.67)	(0.95)	(1.83)
1(Mechanization) X Baseline Area (Acres)	-0.00669	-0.00669	-0.0262***	-0.0443***	-0.0416***
	(-0.79)	(-0.79)	(-2.69)	(-3.08)	(-2.66)
1(Cash and Mechanization) X Baseline Area (Acres)	-0.00566	-0.00566	0.00875	-0.00995	-0.0237
	(-0.55)	(-0.55)	(0.68)	(-0.72)	(-1.42)
Baseline Area (Acres)	-0.0783****	-0.0783****	-0.0795****	-0.0726****	-0.0831****
	(-11.23)	(-11.23)	(-10.25)	(-6.39)	(-7.41)
Observations	4389	4389	4398	4371	4372

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