Mechanizing Agriculture

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Abstract

Economic activity in developing countries is labor-intensive, low-scale, and family run, with substantial family managerial time spent supervising hired labor. We use a randomized control trial that subsidizes access to rental equipment markets to study the impact of the adoption of mechanized practices on labor demand, productivity and managerial span of control. The intervention induces greater mechanization in the upstream production stage, and labor savings concentrated in downstream, non-mechanized stages. The reduction in worker supervision needs increases the span of control and allows households to increase non-agricultural income. We use the experimental elasticities to estimate a structural model where farmers make labor supply decisions in the family enterprise and outside of it. The consumption-equivalent welfare from the intervention amounts to 0.9%. The model provides structural estimates of the marginal return to capital at 8.8%, and the shadow value of family labor, 20% below their outside option in non-agriculture.

JEL codes: D13, D2, J23, J22, J43, O13, Q12

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1 Introduction

Economic activity in developing countries is labor intensive, low scale and mostly family-run (Bloom and Van Reenen, 2010; Akcigit et al., 2020). At the same time, the vast majority of workers are employed in agriculture (Herrendorf et al., 2014).[1] A long tradition in development economics argues that an essential condition for economic development is the adoption of technologies that increase agricultural productivity, releasing workers to other sectors of the economy.[2] However, the existence of contracting frictions in labor may require farmers to pass on profitable labor opportunities in non-agriculture while supervising workers in the field (Bharadwaj, 2015; LaFave and Thomas, 2016). While moral hazard problems are ubiquitous in agricultural labor (Foster and Rosenzweig, 1994), technologies that mechanize agricultural operations may ease their incidence by standardizing output and increasing output observability.

In this paper, we study how the adoption of mechanized practices affects managerial supervision needs, demand for hired workers and productivity in production, as well as labor supply among families that run small-scale enterprises. The impact of mechanization on farmers' managerial time and span of control is a novel channel for the transformative role of capital intensification of labor intensive activities. In partnership with one of the largest providers of rental agricultural equipment in India, we conducted a randomized control trial to increase access to rental markets for mechanization covering 7,100 farmers across 190 villages in the state of Karnataka. Farmers were given a lottery for subsidy vouchers that allowed them to access approximately a third of the average mechanization hours over the agricultural season. Vouchers were valid for all available equipment at custom hiring centers (CHCs) and valid for redemption throughout the season, allowing farmers to both optimally choose the technology and the use of equipment across agricultural stages of production. A subset of treatment farmers were given part of the value of the vouchers in the form of a cash transfer. These cash transfers help disentangle income effects associated to the decline in the cost of capital, as well as measure liquidity constraints that may

[1] Adamopoulos and Restuccia (2014) documents a 34-fold difference in the average land holdings of farms in low and high income countries. Family farmers account for 80% of landholdings in low and lower middle income countries, as reported by Graeub et al. (2016) based on FAO's World Census of Agriculture.

[2] An extensive literature includes Baumol (1967), Timmer (1988), Kongsamut et al. (2001) and Ngai and Pissarides (2007). Gollin et al. (2002) quantify that 54% of the growth in GDP-per-capita across countries between 1960 and 1990s is due to growth in productivity within agriculture alone.

impact mechanization take-up. The relevant technologies being chosen include tractors, and implements such as rotavators, disks, cultivators and harrows. The average farmer uses 6 hours of mechanization services per season with a cost of rentals (including a tractor, fuel and driver costs) amounting to 4.6% of the machinery's purchase price on average across implements.

We combine transaction-level data from our implementation partner and survey data to measure the effects of the mechanization rental vouchers. During the intervention, we find that treatment farmers are 30p.p. more likely than control farmers to rent agricultural equipment from the CHCs. Treatment farmers increase mechanization of the their fields by 0.12 standard deviations (intent to treat estimates), which translates into an additional 1.4 hours per acre. We also find that giving a portion of the voucher in cash has the same effect on mechanization as giving the entire amount as a voucher subsidy. This mechanization occurs entirely at land-preparation, which is the mechanized stage at baseline, with 99% of the sample reporting no mechanization on downstream production stages. We find that mechanization lowers labor demand across all farming stages, and disproportionally so in stages not being mechanized; at the same time, the magnitude of the savings in worked days are different for hired and family labor.

We investigate the mechanisms for the differential effects on types of labor using detailed data on task specialization, at the household and individual level. First, we document that in our setting there is substantial task specialization across family vs. hired labor, with nearly 90% of households reporting supervision being done by family male labor, and only about 3% of households reporting hired male labor engaging in supervision. This is consistent with task specialization arising due to the presence of contracting frictions for hired labor like moral hazard. Second, we find that the span-of-control in the farm, measured as the number of hired workers per supervising family member increases by 6.4p.p. in response to the subsidy. Third, households' non-farm income for treatment households increases by 3.6% relative to control farmers consistent with shifts in labor supply outside agriculture, though the latter effect is noisier.

To isolate and quantify the channels through which mechanization subsidies affect family labor supply decisions, hired labor demand and the managerial span of control, we build a structural model of farming and labor supply decisions. Farming is a multi-stage production technology where land preparation can be performed with machines or with labor, as in a standard model of task-replacement (Acemoglu and Zilibotti, 2001). Farmers choose consumption and whether to work in the farm or in non-agriculture in multiple periods. We use the reduced form estimates from the experiment and the structural predictions of the model to compute key outcomes for the role of subsidized mechanization services at scale. In particular, we measure the marginal returns to capital and the shadow value of family labor on the farm, which is inherently unobservable. [3] We find that the marginal returns to capital are 8.8% per season under the assumption of frictionless rental markets.[4] The model also shows that the shadow value of family labor is 20% below their outside option in non-agriculture, a gap that is consistent with contracting frictions that tie family workers to the operation of the farm, i.e. moral hazard.

We further exploit the structure of the model to rationalize a null effect on output per acre (and profitability) that we find experimentally.[5] We compute the residual (endogenous) productivity change that is consistent with the reduced form responses in employment, capital and value-added, and measure an increase in total factor productivity of 6.6% per season. Finally, we use the model to assess farmers' welfare changes from the intervention. Because the interventions shifts incentives to work in non-agriculture and farming households' optimal leisure allocation across all stages of production, income changes are not sufficient to assess welfare. We construct a measure of consumption-equivalent welfare for the average farmer and find that the intervention raised welfare by 0.9%. The main contributors to the welfare gains are the changes in total factor productivity mentioned above, followed by the improvement in the span-of-control in the farm and its impact on labor supply decisions.

This paper is related to three main literatures. First, to our knowledge, this is the first experimental evidence of the impact of mechanization, as well as access to capital rental markets.[6] Importantly, we provide and quantify the role of output standardization associated to mechanized practices. Output standardization is valuable in environments with moral hazard problems, where family/managers'

[3]In our setting, like most small-scale agriculture and micro-enterprises, family labor is unpaid.

[4]The marginal returns to capital can be as high as 15.5% when allowing for frictions in these markets, as discussed in section 7.1

[5]The effects are positive but noisily estimated.

[6]We document a labor displacement effect consistent with capital-labor substitution emphasized by the automation literature, (Acemoglu and Restrepo (2019) and papers there cited). There is a growing literature studying the impact of automation on firm's output and labor that has mostly focused on developed economies, and that founds mixed evidence including Aghion et al. (2020); Chandler and Webb (2019); Humlum (2019); Koch et al. (2021).

effort is devoted to worker supervision, (Bharadwaj, 2015; LaFave and Thomas, 2016; Foster and Rosenzweig, 2017). We document how mechanization allows farmers to reduce supervision effort and increase their span-of-control, and to take advantage of profitable outside options in non-agriculture.[7] These findings provide direct evidence for theories of disparities in operation sizes between poor and rich countries that include contracting frictions, including Bloom and Van Reenen (2010) and Akcigit et al. (2020).

Second, our paper contributes to the literature on causally estimating the marginal returns to capital in developing economies. De Mel et al. (2008) estimate the marginal returns to capital in microenterprises in Sri-Lanka and Karlan et al. (2014) estimate the returns to farm profitability in Ghana when cash grants are provided (as well as insurance). The results on returns to capital using cash grants are mixed, with De Mel et al. (2008) finding large returns for micro-enterprises, and Janes et al. (2019) finding greater TFP from this same intervention, but Karlan et al. (2014) finding no impacts for small farmers in Ghana. We estimate the returns to large mechanized equipment via rental markets, since the small size of operations make ownership of these equipment largely not cost-effective. Our findings show that while there is no impact on revenue or profitability, capital deepening via mechanization in upstream production stages is strongly labor substituting across all stages, and relaxes contracting frictions for hired labor. [8] We show that in an environment where capital-deepening affects total factor productivity endogenously, randomized variation in the cost of capital is not enough to identify marginal returns. We make a methodological contribution showing how to overcome this obstacle, by using identification restrictions from our structural model.[9] The quantitative assessment of different channels for labor demand and supply decisions through the structural model is akin to Buera et al. (2020), who use a general equilibrium model to interpret the effect of microfinance programs.

Third, we document the impact of mechanization for labor reallocation away from agriculture into non-agriculture. There is an extensive (and mostly theoret-

[7]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.

[8]There is also a related non-experimental literature estimating the returns to land in agriculture (Udry and Anagol, 2006; Bardhan, 1973; Foster and Rosenzweig, 2017).

[9]The combination of quasi-experimental evidence with structural macro models was pioneered by Kaboski and Townsend (2011) and has recently been expanded to include experimental evidence, including migration subsidies Lagakos et al. (2018) and infrastructure Brooks and Donovan (2020).

ical) literature on the role of capital deepening for structural change, including Acemoglu and Guerrieri (2008); Alvarez-Cuadrado et al. (2017), although quantitative measures remain elusive.[10] The role of capital intensification for agricultural productivity has been studied in Caunedo and Keller (2020) and Chen (2020) through accounting exercises. We provide the first available evidence of key micro-elasticities of interest to assess the role of mechanization subsidies at scale, i.e. the marginal return to capital and the shadow value of family labor.

2 Setting and Experimental Design

We conducted the experiment in 190 villages across eight districts in Karnataka.[11] Farmers in this region, like in most developing countries, are engaged in smallholder agriculture. The median land cultivated is 2 acres, and the most common crops are paddy (rice), cotton, and maize. Most farmers engage in rental markets: over 80% reported renting some equipment at baseline.Farmers can rent equipment from other farmers in the same village (informally), or use custom hiring centers (CHC), which our implementation partner —the largest provider of such services in the country— has established across the state (formal rental). For the latter, the farmer places a rental order using a phone number, and receives the equipment with a driver. The only production stage that is mechanized is the most upstream production stage, land preparation, with less than 2% of households reporting mechanization in a downstream stage.

The experiment is a two-stage randomized controlled trial. The first stage of randomization is at the village-level, and the second is at the farm-level. Surveyors started from a central point in the village and went door to door. Farmers were recruited into the experiment conditional on being interested in a lottery for subsidized mechanization rentals– conditional on being approached, over 99% of farmers agreed to being in the lottery. After the baseline survey was administered, farmers were given a scratch card which either did not include a discount (comprising the control group), included a discount for renting any equipment at a CHC, or included a partial rental discount and the value of

[10] Applied work by Bustos et al. (2020) emphasize the role of factor-bias technology to reconcile the adoption of technology in agriculture with the reallocation of labor away from it in open economies. Arguably, the adoption of mechanized practices is among the most salient forms of factor-biased technical change.

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

the remaining voucher as an unconditional cash grant. Farmers with subsidy vouchers could call a nearby CHC, request a rental service and get a discount of up to the full subsidy amount from the rental cost. The vouchers were valid between June and November 2019, spanning the main agricultural season (kharif) and the early 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. We provided these lists and phone numbers to ensure that all farmers had identical information about the CHCs, and so we can interpret the treatment effects as resulting from the subsidy. The exact amount of the rental discount varied, as did the cash grant.

A farmer's demand for mechanization services is a direct function of the cultivated land. For example, the farmer either prepares the seedbed in a plot with machines or with labor, and if it uses machines, it requires machine hours proportional to the size of the plot. The size of the subsidy was therefore set to be larger for farmers cultivating larger plots so that the value of the discount relative to their demand were comparable across land holdings. The size of the voucher for small land holders (less than 4 acres) was calibrated using rental records from our implementation partner (discussed in detail in Section 3.1) to amount to approximately two rental hours of a rotavator/cultivator, i.e. the two most commonly rented implements. This is the median use per transaction in the administrative data for a plot size of two acres, the mean land-holdings for farmers servicing less than 4 acres. The size of the voucher for large land holdings (more than 4 acres) amounted to 3 hours of service on average. In addition, we varied the size of the voucher within land holding category to explore the presence of non-linearities in responses to the subsidy, for example, economies of scale.

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.[12] Farmers who received cash grants received half the value of the rental subsidy in the form of a voucher, and half the amount in cash (₹1050 in cash for small farmers and ₹1750 in cash for large farmers). More details on sample sizes and subsidy amounts can be found in Table C3.

Villages were either assigned to the high intensity arm (70 villages), low

[12] While vouchers could not be combined in a single transaction, they were valid for multiple transactions of the same farmer, and could be easily transferred to other farmers.

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 received the rental price subsidy, 6 farmers received part of their voucher as a 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 part of their voucher as cash grants. The control villages surveyed 20 farmers in each village. In total, about 7100 farmers were part of the intervention.

3 Data and Reduced Form Empirical Strategy

3.1 Survey Data

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– only 12.5% of households reported a fourth member working in agriculture, so this restriction does not exclude an important fraction of household farm labor. Finally, we collected data on income from other sources, including working as agricultural labor on others' farms and nonagricultural income at the household level.

Due to fieldwork restrictions to minimize the risk of Covid-19 spread, the endline survey was completed for about 5500 households. Prior to this, we had universal compliance in participation in the endline. Table 1 shows that the take-up of mechanization services 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. This is consistent with the fact that partial completion of the endline survey was due to the research team deciding to cease fieldwork, rather than selection into survey response. We were able to conduct a brief follow-up phone survey, and were able to survey 93% of the sample either in-person or over the phone. The phone survey was significantly shorter and only covered some key variables–wherever available, the estimates obtained from pooling the surveys are within sampling error of using the detailed in-person surveys, and so we use the latter estimates throughout. The probability of ever being surveyed is reported in Table C2, and is balanced across treatment groups, though there is a small difference in the probability of being surveyed in person.[13]

3.2 Administrative Rental Records

We combined the survey 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. We use the administrative data to measure both take-up and leakage i.e. checking whether farmers that were given vouchers give them away to other farmers.

3.3 Census

To examine the external validity of our results relative to the population of farmers in this area, we run a Census of farming households, covering 41,000 farmers in 150 villages. Table C5 presents summary statistics from the intervention sample, and the census data collection. The samples are largely comparable, though intervention households are slightly smaller than their population's counterpart.

3.4 Reduced Form Estimation

Our main estimating equation is as follows:

$$\begin{aligned} y_i &= \alpha + \beta \mathbb{1}[\text{Mechanization Voucher}_i] + \gamma \mathbb{1}[\text{Partial Mechanization Voucher in Cash}_i] \\ &\quad + \psi_1 y_{ib} + \psi_2 X_v + \epsilon_i \end{aligned} \tag{1}$$

[13] To ensure our results are not impacted by this disruption, we also estimated an alternative version of the treatment effects. We estimate the inverse probability of being surveyed on treatment dummy variables interacted with household characteristics —including 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— and weight all our final estimates with the inverse probability weights. We find that unweighted estimates are nearly identical to the weighted estimates, and so omit them here.

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. $\mathbb{1}[\text{Partial Mechanization Voucher in Cash}_i]$ is a binary variable that takes the value 1 if the farmer received their voucher partially as a subsidy voucher and partially a cash transfer, and is 0 otherwise. y_{ib} denotes baseline controls, wherever available. X_v 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. Parameter β identifies the impact of being given a rental subsidy voucher, and γ the *additional* effect of being given the subsidy voucher partially as cash. Intent to treat (ITT) estimates are presented throughout the paper, though as discussed in the next section, Table 1 presents take-up estimates. Standard errors are clustered at the village-level.[14]

Since we are unable to reject that vouchers of different amounts had statistically different effects (see Table C7), all voucher subsidy treatments were pulled together to maximize power following our pre-analysis plan.

4 Reduced Form Experimental Results

4.1 Mechanization Use

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.[15] 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 30p.p., a highly statistically significant effect. These results are identical when restricting the sample to those farmers for whom the endline survey was completed. Giving part of the voucher in cash has a small negative marginal effect on this outcome (of 3p.p.). On average, treatment households received about ₹2550 in subsidies, and conditional of using the CHC rental, redeemed on average rentals of about ₹2000– thus, conditional on take-up, they used most of

[14] The most comprehensive matching technique that includes phone numbers as well as respondent names and their family members' names leaves only 1.3% of redeemed vouchers unmatched, indicating that there is low leakage of the vouchers.

[15] Less than 5% of the households report a non-unique phone number, a behavior that is uncorrelated with treatment status. Alternative measures that use phone number as well as name matching, yield identical treatment effects.

the available subsidy, and do not add in additional funds of their own.

Table 1: Take-Up

	(1)	(2)	(3)	(4)	(5)	(6)
	1(Matched to Platform)					
1(Mechanization)	0.304****	0.333****	0.304****	0.332****	0.307****	0.336****
	(0.0160)	(0.0177)	(0.0172)	(0.0191)	(0.0166)	(0.0182)
1(Cash and Mechanization)		-0.0611****		-0.0605****		-0.0603****
		(0.0158)		(0.0166)		(0.0159)
Control Mean	0.11	0.11	0.11	0.11	0.11	0.11
Observations	7202	7161	5530	5492	6679	6638
Sample	Full		In-Person		In-Person/Phone	

Notes: Standard errors clustered at the village-level in parentheses.

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

The dependent variable takes the value 1 if a farmer's phone number in the survey data could be matched to the mechanization rental platform data, and 0 otherwise.

Table C6 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 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.

Overall mechanization rental. We rely on survey data to understand whether rental vouchers increase participation in the CHC rental market by merely substituting mechanization rentals from other providers or if they increase overall mechanization. We asked farmers about hours rented for each implement at different stages of production. All implement-wise hours are standardized (by subtracting the mean and dividing by the standard deviation), and added together. This is our total mechanization rental variable. Such a standardization allows us to aggregate hours rented across implements for which farmers have heterogeneous average needs in farming activities. For example, given a plot size, the average hours needed for a sprayer to complete a task may be different from the average hours needed for a rotavator to complete another task. We divide the mechanization rental variable by the cultivated area to construct our mechanization index per acre. We similarly standardize the mechanization index to allow us to interpret the effect of treatment in terms of standard deviations of the dependent variable. Finally, we take the inverse hyperbolic sine (IHS) to dampen the effect of outliers.

We find that rental markets for mechanization are prevalent for land preparation only, the first stage in production, i.e. less then 2% of the sample reports renting mechanization in other stages.[16] Therefore, while we report results for total mechanization hours, these should be interpreted as changes to land preparation mechanization.[17]

Results are presented in Table 2. 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 by 1.4 hours per acre in mechanization, or 4.5 total hours on average (at mean land cultivated, about 3.3 acres). Giving part of the voucher as cash does not have any differential effect in mechanization relative to the giving the entire subsidy as a rental subsidy.

Table 2: Mechanization Index Treatment Effects

	(1) IHS (Mechanization Index)	(2) IHS (Mechanization Index)
1(Mechanization)	0.135****	0.159****
	(0.0356)	(0.0406)
1(Cash and Mechanization)		-0.0523
		(0.0374)
Control Mean	-0.0500	-0.0500
Unstandardized Control Mean	6.4	6.4
Observations	4989	4989

Notes: Standard errors clustered at the village-level in parentheses.

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

The dependent variable is the inverse hyperbolic sine of the mechanization index. The index is constructed by standardizing all implement-wise hours, summing them, and dividing by area cultivated.

4.2 Farming Labor

Mechanization of any productive activity has direct impacts on labor use via several different channels. Mechanization can be labor saving, by directly replacing workers in certain tasks, i.e. a substitution effect; or it could increase labor demand by improving overall productivity and the scale of production, i.e. a scale effect. To identify the impact of the subsidy on capital on labor, we measure labor inputs as the number of working days per acre for four types of workers – family male labor, family female labor, hired male labor, and hired female labor. This classification yields variation in labor demand by gender and

[16] Ownership rates for the relevant equipment are less than 3% in our sample.

[17] Table C8 presents treatment effects for land preparation only, and shows very similar treatment effects to considering overall mechanization.

for family vs. non-family workers. Demand for hired labor has been shown to depend on family labor availability, which in combination with the fact that family labor is overwhelmingly more likely to engage in supervision, indicates the presence of contracting frictions in hired labor (Bharadwaj, 2015; LaFave and Thomas, 2016). Furthermore, tasks in agriculture are also specialized by gender in many contexts, including this one (discussed in detail in Section 4.3 and Table 4). Therefore, mechanization is likely to have differential effects by type of labor: gender as well as hired vs. family labor.

Results are presented in Table 3. Family labor declines by similar magnitudes across gender, 16p.p. for males and by 16.6p.p. for females. These declines amount to 2.3 days of male family labor and 1.5 days of female family labor per acre. Hired labor displays heterogeneous effects by gender, with no significant shifts for males and a decline in female hired labor of 11.6p.p., significant at the 5% level. The decline in female hired labour amounts to 4.4 days of work per acre. This overall effect includes labor use across mechanized production stage (land preparation) and unmechanized production stages (all other downstream stages, namely, planting, plant protection, harvesting, and post-harvest processing). Next, we present results for labor demand separately by the mechanized stage (land preparation), and downstream, non-mechanized stages (combined labor demand for planting, plant protection, harvesting, and harvest processing). The second and third panel of Table 3 presents these results: we find that the treatment displaces primarily family labor for the mechanized stage, with little change for hired labor, either male or female. Mechanization reduces family male labor by 0.3 days per acre (10 p.p), and female family labor by about 0.07 days per acre (7.7 pp). For downstream stages, we find that while mechanization is labor substituting for all types of labor, the magnitude of the impact varies substantially by type of labor. For male labor, the effects are similar for family vs. hired male labor i.e. the treatment decreases demand for family male labor by about 1.7 days per acre (13 p.p.), and for hired male labor by about 1.3 days per acre (5.7 p.p.). In contrast, the effects are quite different for female labor–mechanization reduces demand for family female labor by about 1.1 day per acre (13.9 p.p), and by female hired labor by over 3 times more, about 4.2 days per acre. [18]

[18]In the appendix, we present results for both the binary probability that a particular type of labor works on the farm (Table C11),, as well as an alternative measure of intensive margin labor demand, i.e. the number of workers per acre (Table C12). These tables show that the treatment does not impact the binary probabilities of different types of workers working on the

Table 3: Labor Use Per Acre: Treatment Effects

	Entire Season			
	Family Male	Hired Male	Family Female	Hired Female
	(1)	(2)	(3)	(4)
1(Mechanization)	-0.160****	-0.0504	-0.166****	-0.116**
	(0.0474)	(0.0461)	(0.0434)	(0.0499)
1(Cash and Mechanization)	0.0183	-0.0250	0.0396	0.0778
	(0.0495)	(0.0581)	(0.0500)	(0.0617)
Control Mean Levels	14.53	27.76	9.040	38
Observations	5525	5533	5526	5533
	Land Preparation			
	Family Male	Hired Male	Family Female	Hired Female
	(1)	(2)	(3)	(4)
1(Mechanization)	-0.105***	-0.0157	-0.0770****	-0.0157
	(0.0359)	(0.0403)	(0.0211)	(0.0254)
1(Cash and Mechanization)	0.0157	-0.0423	0.0464*	-0.0381
	(0.0387)	(0.0457)	(0.0250)	(0.0275)
Control Mean Levels	3.240	4.830	0.950	1.150
Observations	5458	5492	5444	5442
	Other Stages			
	Family Male	Hired Male	Family Female	Hired Female
	(1)	(2)	(3)	(4)
1(Mechanization)	-0.133***	-0.0572	-0.139***	-0.116**
	(0.0467)	(0.0512)	(0.0433)	(0.0492)
1(Cash and Mechanization)	0.00708	-0.0156	0.0244	0.0880
	(0.0494)	(0.0640)	(0.0516)	(0.0601)
Control Mean Levels	11.33	22.96	8.100	36.89
Observations	5525	5533	5526	5530

Notes: Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
The dependent variables are the inverse hyperbolic sine of days of labor use per acre.

4.3 Task Specialization and Impacts on Managerial Span of Control

Why do the effects of mechanization vary by family vs. hired labor and by gender? In this section we show that differential task engagement by labor types is the primary source for this heterogeneity. We construct two measures of labor engagement. The first one collects information on all tasks ever performed by different types of labor while the second one only uses information on the

farm. The results on the number of workers per acre are consistent with our main measure of labor demand (the number of days per acre).

tasks-listed-first for each type of labor.[19] Table 4 shows that tasks performed by different types of labor vary substantially, and Table C9 shows that the task engagement results are strikingly similar across measures.

Supervision tasks are primarily conducted by male family labor, followed to a much lesser extent by female family labor. Male family labor is more likely to engage in input sourcing and marketing, both relative to their female counterparts and to hired labor. Several other tasks are gendered rather than segregated across family versus non-family labor – for instance, weeding and transplanting are primarily performed by women, whereas land preparation and manure application are primarily done by men. This task specialization and the differential impact observed on hired workers in other stages of production is suggestive of the impact of mechanization of land preparation on other tasks within the farm.

Family labor engagement in supervision activities is consistent with moral hazard problems in farming activities. It also highlights the role of family size, a type of labor with low or no moral hazard problems, for labor demand decisions (e.g. Bharadwaj, 2015). The differential task engagement for family and non-family workers suggest that our study is also informative for the optimal operating scale of production in environments where there are frictions in delegation (e.g. Akcigit et al., 2020).

[19] The first one 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 4: 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

Notes: The table reports the likelihood that a worker of a given type, e.g. family/hired or male/female, reports engaging in a task using the end-line survey data i.e. 87.87% of households report family male labor engaging in supervision, whereas only 3.13 households report hired male labor doing so.

Supervision and span of control. Given that farms are overwhelmingly managed by male family labor, we now test how the labor effects of the intervention impact the span of control on the farm. To measure the span of control on the farm we bring in task-engagement data at the individual level. For each household, we ask all tasks that each household member performed on the farm, for up to four members most engaged in agriculture. [20] We use this data to construct two measures of the span of control. The first is the number of hired workers per household member who reported supervision as one of the tasks they performed on the farm.[21] The second is more directly linked to our measures of labor demand, i.e. the total number of days per acre of hired labor, divided by the number of days worked on the farm by household members that report supervision as one of their tasks.

Table 5 show that the span of control increases in response to treatment by 6.5p.p., i.e. there are additional 1.6 hired workers per family male supervising worker. Table C10 shows results for the number of worker days, and shows that treatment increases the number of hired labor days per supervising household

[20]Only 12.5% of households report a fourth member, indicating that we are measuring tasks performed by a large proportion of members for most of our sample.

[21]This is a standard measure of the span of control, i.e.the number of workers supervised by a manager Bloom et al. (2014).

member days by 0.5. 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. Second, if lower labor demand for mechanizable tasks also induces a decline in family labor by for example, reducing the incidence of moral hazard, the span-of-control may increase. In our experiment, this second effect is greater than the direct effect of the labor-saving technology. Deep and multiple rounds of tillage during land preparation both lowers the prevalence of weeds, as well as ensures that planting happens in consistent rows, so that subsequent operations are easier to monitor. We link the improvement in the span of control and the decline in hired female labor, which mostly engages in weeding, as evidence of output standardization.

Table 5: Span of Control: Workers per supervising family member.

	(1)	(2)	(3)	(4)
	Span of Control		IHS(Span of Control)	
1(Mechanization)	1.185*	1.685**	0.0591**	0.0644**
	(0.666)	(0.787)	(0.0258)	(0.0308)
1(Cash and Mechanization)		-0.999		-0.0104
		(0.786)		(0.0336)
Control Mean Levels	24.95	24.95	24.95	24.95
Observations	4939	4903	4939	4903

Notes: Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
The span of control is the number of hired workers per household member reporting supervision as one of the tasks they performed on the farm. Columns 1 and 2 report results in levels, and columns 3 and 4 for the IHS of span of control.

4.4 Returns on the Subsidy

Before moving the structural model it is useful to compute the monetary returns on the intervention. These returns stem from changes in farm profitability (either by an increase in revenue or a decline in input expenses). We study each one in turn and report returns at the end of the section.

Revenue and profits. In this section, we show treatment estimates for farming revenue and profits. We measure profit via a survey question which asks farmers how much money they had left over from farming income after paying all expenses.[22] Since revenues are measured conditional on selling output,

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

test whether the probability sells output is impacted by treatment–results are presented in Table C15, and show this is not the case.[23] We also construct a measure of revenue that adds reported costs to the money left over from farming reported by households (the measure of profit). There is no effect on revenue from the treatment either.[24]

Results for revenue and profit per acre are presented in Table C16.We find that treatment has no significant impact on revenue or profits per acre. This also helps rule out direct income effects as the reason for the changes to labor demand. When we consider potentially disparate effects of cash, we again find no significant impact in either outcome.

Input expenditures. In addition to changing the pattern of labor use, mechanization may impact input intensification shifting expenses in intermediate inputs. Table 6 tests this hypothesis. Input expenditures are the sum of expenditures on seeds, irrigation, fertilizer, manure, animal labor, and other plant protection inputs. The outcome variable is the IHS of input expenditures per acre. We find that mechanization reduces raw material expenditure, with no marginal impact of giving part of the voucher in cash.

Table 6: Other Input Expenditures: Treatment Effects

	(1) Fertilizer	(2) Manure	(3) Plant Protection	(4) Irrigation	(5) Seeds	(6) Total Expenses
1(Mechanization)	-0.0915	0.0466	-0.0423	-0.0223	-0.103	-0.131***
	(0.0560)	(0.125)	(0.100)	(0.113)	(0.0772)	(0.0475)
1(Cash and Mechanization)	-0.00304	-0.0401	0.162	-0.104	-0.0261	0.0364
	(0.0651)	(0.160)	(0.101)	(0.124)	(0.0856)	(0.0542)
Control Mean Levels	4630.1	755.6	1933.8	472.6	1593.8	9590.6
Observations	5443	5453	5440	5441	5365	5495

Notes: Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
Dependent variable is the inverse hyperbolic sine of each type of input expenditure per acre.

Returns on the subsidy. Equipment subsidies accounted a third of the average mechanization hours reported for the control group, the equivalent of 2 hours of rotavator usage and 2.5 hours of cultivators usage evaluated at market prices. To compute the returns on the subsidy we add savings in farming expenses associated to treatment as a share of the average subsidy allocated to farmers, ₹2418 given the voucher distribution. We find evidence of savings in intermediate

[23]We also test for, and do not find any effects on the proportion of output sold in the market.
[24]Results using market revenues only also show no effect of treatment. Alternatively, we can test for the impact on yields, which also do not show an effect of treatment.

inputs (a decline of 13% on average per acre) which are the main drivers of these returns. Average savings on capital and labor as well as profits improvements are noisily estimated and therefore omitted, see table C14. We estimate a return on the subsidy of 77% for the average farmer who holds 3.3 acres of land. The largest savings in intermediate inputs stem from lower expenses in fertilizers, albeit the point estimate is noisily estimated.

4.5 Nonagricultural Income

Finally, to the extent that farming households can take advantage of lower needs for their own time in the farm by taking opportunities in other activities, the above returns underestimate the income gains from the intervention.

We test whether unpaid family labor released from the farm is reallocated to activities in other sectors of the economy. Table 7 examines the effects of treatment on household-level nonagricultural income. 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 7: Non-Agricultural Income: Treatment Effects

	(1) 1(Any Non-Agricultural Income)	(2) IHS(Non-Agricultural Income)	(3) Change in IHS (Non-Agricultural Income)
1(Mechanization)	0.0183	0.204	0.464**
	(0.0147)	(0.154)	(0.207)
1(Cash and Mechanization)	-0.00207	-0.00768	-0.0144
	(0.0168)	(0.172)	(0.239)
Control Mean Levels	0.310	6882.0	533.7
Observations	5497	5468	5409

Standard errors clustered at the village-level in parentheses.

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

1(Any Non-Agricultural Income) is a binary variable that is 1 if the household reported income from non-agricultural sources, and 0 otherwise. IHS(Nonagricultural income) is the inverse hyperbolic sine of the level of household income from nonagricultural sources.

5 A Model of Farming, Mechanization, and Labor Allocation

Next, we present a model to interpret the average effects of the experiment. The combination of the model and our experimental design allows us to identify key parameters of interest for future studies of the impact of subsidies at scale, including the returns tocapital, the shadow value of unpaid family labor and the friction associated to workers' moral hazard. Importantly, we can compute welfare gains associated to the mechanization of production. These gains depend on the farmers' engagement on the farm (for supervision or productive purposes) and on the outside option to farming households, through labor opportunities in other farms as well as non-agriculture, which affect the opportunity cost of leisure.

The economy is populated by a continuum of identical farming households, each of which is endowed with $\bar{n}$ units of time per period.[25] Family workers elastically supply labor for farming activities or for activities outside the farm. Each household is endowed with a plot of land of size, l.

Farming entails two stages: land preparation, *preparation* henceforth; and planting, plant protection, harvesting and processing, *harvesting* henceforth. Output from the preparation stage is used as an input for the harvesting stage. Farmers use land, capital and labor to produce, and take input prices as given. Whereas both capital and labor are used to complete these stages, our empirical findings suggest that the intervention affected mechanization practices at the preparation stage only.[26] Therefore, we simplify the exposition and assume that harvesting activities are only performed with labor. Finally, there is moral hazard in hired labor, and therefore workers need to be supervised.

Through the lens of this model, our intervention generated an exogenous shift in the cost of mechanization hours, which we analyze in Section 5.5.

5.1 Farming Households

A farming household derives utility from consumption, c^j, and leisure, n_l^j in each stage $j = \{P, H\}$, with preferences that satisfy standard concavity and Inada

[25]Differences in household's size have direct impact on the endowment of time available to them.

[26]Indeed, mechanization expenses outside land preparation account for less than 2% of our control sample.

conditions, $U(c^j, n_l^j)$. Family time $\bar{n}^j$ in each stage is assumed exogenous, and can be devoted to leisure, n_l^j, to working on the farm, n_f^j, to supervising workers on the farm, n_s^j, or to working outside the farm, n_o.

$$n_l^j + n_f^j + n_s^j + n_o^j = \bar{n}^j. \tag{2}$$

Family income for farming households includes income from working outside the farm at wage w_o, plus the revenue from farming, net of capital and hired labor costs. The profits from farming π include the returns to the land that farmers own, as well as any unpaid family labor on the farm.[27] Farming households consume over two periods and discount future consumption at the market interest rate, $R > 1$.[28] We assume no working capital constraints, so factors are paid at the end of the season, once agricultural output has been realized.

$$c^P + \frac{1}{R}c^H = w_o n_o + \frac{1}{R}\pi. \tag{3}$$

Importantly, the supply of capital is exogenous to the farming sector, consistently with the low ownership rates for agricultural equipment observed in our data.[29]

5.2 Farming Technology

Let the size of a plot be l, capital services k, family labor n_f, and hired labor, n.[30] To study the main channels through which a mechanization subsidy affects labor, we distinguish between family and hired labor and we abstract from worker gender. This demographic characteristic is introduced again when parameterizing the model. The main difference between family and hired labor is that the latter has incentives to shirk and exert no effort while at work. Therefore, hired labor produces positive output only if supervised at rate s.

Preparation stage. Output from the preparation stage, y^P, is a Cobb-

[27] Fewer than 2% of households report farming land that is not owned by the household.

[28] For simplicity, we assume all non-farm labor engagement occurs when farm labor demand is low, i.e. at the land preparation stage. The model can be readily extended to allow engagement in both periods.

[29] Ownership rates are extremely low in our sample, with less than 2% of the sample owning any rotavators or cultivators. Most rental services are provided by specialized firms, like our implementation partner, which are not directly engaged in farming activities.

[30] Intermediate inputs in production, and the expenses associated to them are fully accounted in the quantitative exercises. For simplicity, we pose a value added specification for the farming technology.

Douglas function of land and tasks, i, that can either be performed by a machine, supervised hired labor, or family labor. There is a continuum of measure one of these tasks. Therefore, output from the preparation stage follows,

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

where $\alpha_l = 1 - \alpha$, and input from each task is

$$x(i) = a_k(i)k(i) + a_n(i)n^P(i,s) + a_n(i)n_f^P(i).$$

where n_f^P, n^P labels family and hired labor at the preparation stage, respectively. For simplicity, we assume that the marginal product of a unit of labor in the completion of each task i is the same whether performed by family or hired labor, $a_n(i)$. The marginal product of a unit of capital services is $a_k(i)$. We assume the following pattern of bias of technology between labor and capital,

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

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

Harvesting stage. Output in the harvesting stage, y^H —i.e. final output $Y \equiv y^H$— is a Cobb-Douglas aggregator of labor, land and output from the preparation stage.[31] To allow for shifts in labor needs due to mechanization of land preparation, we introduce a labor requirements shifter, $b(I)$, as follows

$$y^H = y^P(\min\{n_f^H, b_f(I)\})^{\alpha_f^H}(\min\{n^H, b(I)\})^{\alpha^H} l^{\alpha_l^H}.$$

where the requirements function is assumed proportional for family and hired labor, i.e. $b_f(I) = b(I) + \bar{b}$ for some constant $\bar{b}$, possibly negative. The level shifter in requirements generates disparities in average engagement between family and hired labor at the harvesting stage. The labor requirements function allows us to accommodate disparate shifts in labor across stages despite the Cobb-Douglas production structure. These requirement may include, for example,

[31] We abstract away from uncertainty in returns to agricultural activities, typically linked with weather shocks, (Rosenzweig and Udry, 2014). The adoption of mechanized practices at land preparation had no direct impact on return uncertainty through weather shocks. One potential channel though which it may shift this uncertainty is by inducing the switch of crops towards more resistant varieties. Our intervention did not impact crop choice, therefore we abstract away from this channel.We omit these results for brevity but they are available upon request.

lower weeding needs after mechanized land preparation.

5.3 Contracting Problem

Workers effort in the field is not observable, and hired labor can exert effort or shirk. If a worker shirks, she gets a benefit proportional to the market wage, ωw. Therefore, ω is a measure of the incidence of the friction, i.e. the incentives to the worker not to exert effort. Family workers can supervise workers, in which case they can catch a shirking worker with probability $\min\{\frac{n_s}{n}, 1\}$. Hence, the probability of catching a shirking worker increases with family labor engaged in worker supervision, n_s. Then, a standard incentive compatibility constraint implies that hired labor does not shirk if and only if the wage he gets is weakly higher than the expected return from shirking,

$$w \geq \omega w + \left(1 - \frac{n_s^j}{n^j}\right) w,$$

assuming, $\frac{n_s^j}{n^j} \leq 1$ for each stage $j = P, H$. If the worker shirks, no hours are allocated to production.

5.4 Optimal Allocations

Preparation stage. The optimal allocation of inputs to tasks given prices is such that the value of the marginal product for hired workers is the same irrespective of the task they perform. The optimal allocation of family labor and capital across tasks also shares this feature. Given Assumption 1, 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 or family labor **?**. If the shadow value of family labor is below the shadow value of hired labor —i.e. market wages in agriculture plus supervision time— optimality requires that family labor is exhausted before engaging hired workers. In other words, the ratio of non-family to family workers is endogenous and depends on prices, the family labor endowment $\bar{n}$ and their outside option, e.g. non-agricultural opportunities.

An implication of optimality 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. Hence, factor allocations are the same across tasks produced by the same input. If I is the threshold for mechanization, the optimal allocation of hired labor is $n^P(i) = \frac{n^P}{1-I}$, that of family labor is $n_f^P(i) = \frac{n_f^P}{1-I}$, and the one of capital is $k(i) = \frac{k}{I}$, where n_f^P, n^P and k are the total amounts of family labor, hired labor and capital services used in the farm at the preparation stage, respectively.

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

$$y^P = A^P k^{\alpha I}(n^P + n_f^P)^{\alpha(1-I)} l^{\alpha_l^P}.$$

where $A^P = \bar{a}_k(I)\bar{a}_n(I)$ is an endogenous productivity term that depends on the mechanization threshold and the bias of technology (a_k, a_n). [32] Given the above technology, we can solve for the optimal demand for family labor, supervised labor, capital in the farm as a function of the threshold I. Standard optimality conditions yield the key predictions for input allocations (see Appendix A).

Harvesting stage and final output. We can combine output from the preparation stage with factors used for harvesting to construct a measure of final output,

$$y^H = A^P k^{\alpha I}(n^P + n_f^P)^{\alpha(1-I)}(n^H)^{\alpha^H}(n_f^H)^{\alpha_f^H} l^{\alpha_l}.$$

We assume constant returns to scale in inputs, i.e. $1 = \alpha + \alpha_l + \alpha_f^H + \alpha^H$, where $\alpha_l \equiv \alpha_l^P + \alpha_l^H$. The productivity term is a non-monotonic function of the bias of technology. For relatively low levels of mechanization, additional mechanization improves productivity. In the language of the model, capital has a bias of technology over labor for tasks with low indexes. For relatively high level of mechanization, additional mechanization is detrimental to productivity. In the context of the model, labor has a bias of technology over capital for high indexes tasks. In addition, the slope of the change in production varies with the shape of the bias of technology.

Worker supervision. The optimal supervision effort for the family is

$$\frac{n_s^j}{n^j} = \omega \tag{4}$$

Hence, supervision effort is proportional to hired labor in each stage.

Household's labor supply decisions. How much hired labor and family

[32]By definition $\bar{a}_k(I) \equiv \left(\frac{\prod_{i=0}^{I} a_k(i)}{I^I}\right)^{\alpha}$, $\bar{a}_n(I) \equiv \left(\frac{\prod_{i=1-I}^{1} a_n(i)}{(1-I)^{1-I}}\right)^{\alpha}$.

labor gets allocated at each stage depends on the time available to the household and the return to working outside of agriculture. A full description of the equilibrium allocation is included in Appendix C.1. Here we summarize its main characteristics.

Consider an equilibrium where the household engages in farm and non-agricultural production, as in the data. If the wage outside agriculture is weakly higher than that in agriculture, $w_o \geq \frac{w}{1-\omega}$, the cost of hired labor is lower than the cost family labor. Then, while some family labor will be devoted to supervision activities, the rest will be employed outside agriculture. If the opposite holds, then family will be engaged in productive activities within the farm and would only hire workers if labor demand relative to the size of the farming household is high.[33]

Alternatively, the farmer can decide not to engage in either supervision or productive activities at the preparation stage, but then the farm can only produce if fully mechanized. If the cost of capital is high relative to the opportunity cost of working outside the farm, then it will be optimal to partly engage in farming activities, even when the labor premia in non-agriculture is positive $w_o > \frac{w}{1-\omega}$. A full quantitative assessment of different channels affecting equilibrium labor supply is described in Section 7.5.

5.5 Main Experimental Findings Through the Lens of the Model

In what follows, let the value of the marginal product of labor at the preparation stage be $\tilde{w} \equiv w_f$ if $n^P = 0$ and $\tilde{w} \equiv w + \omega w_f$ if $n^P > 0$. Through the lens of the model, the experiment shifted the relative cost of mechanization services relative to the labor input and can be therefore interpreted as a decline in the ratio $\frac{r}{\tilde{w}}$.[34]

Fact 1 *The subsidy induces mechanization.* Higher mechanization can be interpreted through the lens of the model through two channels (1) a higher demand for capital services for a fixed set of tasks; and (2) a higher share of tasks being mechanized. The first channel is well understood and a consequence of the downward sloping demand for capital services. Indeed,

[33] Labor demand is determined by land holdings and farm productivity, holding prices fixed.

[34] A textbook interpretation of a voucher subsidy is that it induces a parallel shift in the farmer's isocost without changing the marginal cost of capital. If this was the case, we should have observed higher demand for both labor and capital associated to a standard scale effect. However, the experimental findings indicate a displacement effect of capital over labor, consistent with a change in the relative cost of capital.

optimality implies higher capital labor ratios in response to the subsidy to the cost of capital, for a fixed mechanization threshold I.

$$\frac{\tilde{w}}{r} = \frac{k}{n_f + n^P} \frac{1 - I}{I} \tag{5}$$

The second channel is particular to a model of optimal task allocation. The marginal condition for mechanized tasks as a function of prices and input demands is

$$\frac{\tilde{w}}{r} = \frac{a_n(I)}{a_k(I)} \tag{6}$$

Therefore, when the price of capital falls due to the subsidy, the marginal mechanized task is higher, $I' > I$ under Assumption 1. Incentives to mechanize tasks are stronger once hiring workers, because those workers are relatively more expensive than family labor.[35] Importantly, the threshold for mechanization is independent of the level of the capital-labor ratio, a consequence of the log-linearity in the task production function.

Fact 2 *Family labor falls at preparation* A lower cost of capital induces mechanization, or a higher threshold I. Lower family labor is a direct consequence of optimality, as follows from equation 5, either because of their farming hours are replaced by machine-hours, or because hired labor falls (albeit noisily estimated) and with it, family supervision time.

Fact 2.b *Family labor falls at harvesting* The optimality conditions for the farmer require that the family input is proportional for both processes, see equations 15 and 18. The increase in the mechanization threshold counteracts this force, increasing the marginal product of labor at the harvesting stage. However, if the elasticity of the threshold to the subsidy is lower than the elasticity of family labor to the subsidy at the preparation stage, then family labor should also fall at harvesting. If in addition, the labor requirements effect of higher mechanization is negative, $\frac{\partial b(I)}{\partial I} < 0$, the demand for labor could decline even further.

Fact 3 *Labor hired at preparation does not change significantly* The point estimates are negative but noisily estimated.[36] The model rationalizes the meager

[35] Note that there is a discontinuity in the effect of the subsidy on the threshold induced by the gap between the cost of hired labor and family labor. At the margin, when $n^P = 0$ the threshold solves $\frac{w_f}{r} = \frac{a_n(I)}{a_n(I)} < \frac{w + w_f \omega}{r}$.

[36] It is worth noting that farms hire few workers at preparation: for 25% of farmers in our

effects on hired labor through the calibrated profile of bias of technology and a relatively high threshold of mechanization at baseline, see Section 6.2.

Fact 3.b *Labor hired falls at harvesting* Optimality requires that hired labor and family labor are proportional at the harvesting stage, see equations 19 and 18. Therefore, if wages for hired workers and family labor do not change, labor hired declines proportionally to family labor.[37] If in addition, the labor requirements effect of higher mechanization is negative, $\frac{\partial b(I)}{\partial I} < 0$, the demand for labor declines even further.

Fact 4 *Revenue per acre does not increase on average* 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

$$\frac{d\frac{y}{l}}{dr}\frac{r}{\frac{y}{l}} = \underbrace{\frac{dA^P}{dr}\frac{r}{A^P}}_{productivity} + \underbrace{(\alpha I)\frac{dk}{dr}\frac{r}{k}}_{intensive-mech} \underbrace{-(\alpha I \ln \frac{k}{n_f^P + n^P})\frac{dI}{dr}\frac{r}{I}}_{extensive-mech} + \underbrace{\alpha(1-I)\frac{d(n_f^P + n^P)}{dr}\frac{r}{n_f^P + n^P} + \alpha_f^H \frac{dn_f^H}{dr}\frac{r}{n_f^H} + \alpha^H \frac{dn^H}{dr}\frac{r}{n^H}}_{labor-replacement}. \quad (7)$$

Equation 7 highlights the key channels through which mechanization affects output per acre. The first one is the *productivity* term which directly relates to the bias of technology of completing a task with a unit of machine services vs. a unit of supervised labor. The second one is the *intensive-mechanization* term, which is standard with a neoclassical production function where price declines generate input intensification and lower marginal product. 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*

sample, own labor supply is enough to cover labor demand at preparation, and for those that hire workers, the average number of hired of workers at land preparation is 1 worker. On average, hired males work 5 days and females work 1 day.

[37] While we found no evidence of changes in market wages, the shadow value of family labor may have. The estimated shadow value of family labor for the calibrated economy, Section 7, is predicted to increase by 0.7p.p. . Absent changes in labor productivity at harvesting, the calibrated economy predicts that the ratio of hired to family labor at harvest declines by 7p.p. in response to treatment, and therefore that hired labor falls more than family labor.

replacement effect. The sign of the intensive-mechanization effect is unambiguously negative, i.e. farmers mechanize when the cost of capital falls. 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 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 bias of technology would determine its magnitude and direction, as we show in Section .

Fact 5 *Non-agricultural income increases* This is a direct consequence of the labor displacement effect of mechanization, and therefore of the savings in family labor on the farm. As we show in Section 7.3, non-agricultural wages are indeed higher than the shadow value of wages on the farm, and therefore it is optimal for farming household to take opportunities in non-agriculture.

6 Identification

6.1 Marginal Return to Capital

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

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

so that the returns to capital are summarized by αI while the returns to capital 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 (summarized by the endogenous productivity term, A^P) and the regressors. De Mel et al. (2008) proposed to use the randomization in access to capital 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 errors (i.e. productivity residuals) are correlated with treatment. Therefore, treatment 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.[38] The optimality condition with respect to capital yields an identification restriction for the share of capital in production, αI which can be evaluated for our control group. The capital share for the control group satisfies,

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

and therefore identifies α conditional on the threshold of tasks performed by machines and labor, I.[39] We discuss this identification next.

6.2 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 the bias of technology, $\frac{a_k}{a_n}$. The identification follows from the optimality of the mechanization threshold, equation 5, in levels and differences; as well as the predicted relationship between the elasticity of output and total factor productivity to treatment, equation 7. The parameters governing the shape of the bias of technology and the mechanization threshold are jointly calibrated to match the elasticity of output-per-acre and the change in the capital-labor ratio and mechanization threshold implied by the experimental elasticities.

From the optimality condition for capital we have,

$$\frac{d\ln(\frac{y}{l})}{d\ln(r)} = 1 + \frac{d\ln(\frac{k}{l})}{d\ln(r)} - \frac{d\ln(I)}{d\ln(r)} \tag{8}$$

Therefore, the difference between the treatment effects on output per acre and capital per acre identify the change in the mechanization threshold. Importantly, one can use the inferred change in the threshold and the treatment effect on capital-labor ratios to identify the level of the threshold, conditional on an assumption on the shape of the bias of technology.

Assumption 2 Let the shape of the bias of technology satisfy $\frac{a_n(i)}{a_k(i)} \equiv \frac{I^{\beta_1 - 1}}{(1-I)^{\beta_2 - 1}}$ for $\beta_1, \beta_2 > 1$.

Let $g(I) \equiv \frac{I}{1-I}\frac{a_n(I)}{a_k(I)}$ measure de equilibrium capital-labor ratio as a function

[38]In a non-parametric approach to estimating production technologies, Gandhi et al. (2020) suggest exploiting the first order conditions associated to firms' profit maximization.

[39]We discuss departures from the assumption of frictionless rental markets in section 7.1.

of the mechanization threshold and the bias of technology.[40] The elasticity of the function g to the movement in the threshold I is a function of the shape parameters, i.e. $\frac{d\ln g(I)}{d\ln(I)} = \frac{\beta_1 + I(\beta_2-\beta_1)}{(1-I)}$, and the level of the threshold. By combining equations 6, 5 and 8 we obtain an identification restriction for the level of the threshold I,

$$1 + \frac{d\ln(\frac{k}{l})}{d\ln(r)} - \frac{d\ln(\frac{y}{l})}{d\ln(r)} = \frac{1-I}{\big(\beta_1 + I(\beta_2-\beta_1)\big)} \frac{d\ln(\frac{k}{n_f^P})}{d\ln(r)}. \tag{9}$$

The elasticity of the productivity residual A^P is a function of the shape parameters β_1, β_2,

$$A^P = \left(\frac{\prod_{i=0}^{I}(1-i)^{\beta_2-1}}{I^I} \frac{\prod_{i=1-I}^{1} i^{\beta_1-1}}{(1-I)^{1-I}} \right)^{\alpha}. \tag{10}$$

Hence, when combined with equation 7, it yields an additional identification restriction for the parameters of interest.

Finally, the threshold condition in levels yields the third identifying restriction for the parameters of interest.

$$\left(\frac{I^{\beta_1}}{(1-I)^{\beta_2}} \right) = \frac{k}{n_f} \tag{11}$$

The threshold and the shape parameters are jointly identified from equation 9, the combination of equations 7 and 10, and equation 11.

There are two challenges in computing the elasticity of the productivity residual to the change in the cost of capital, $\frac{d\ln(A^p)}{d\ln(r)}$. First, such a residual is a function of the cost share of family labor and second, it depends on the elasticity of family productive labor in the farm in both processes, both of which are often times unobservable. To tackle the first challenge we measure the share of family labor as a residual from the share of capital, labor and land, under the assumption of constant returns as described in Section 7.[41] Because capital and hired labor expenses are observable, the share of family labor can be estimated from farm-

[40] This is equivalent to assuming that functional form for the bias of technology is a polynomial of the ratio $\frac{I}{1-I}$, which satisfies Assumption 1. For example, $\frac{a_k(i)}{a_n(i)} = \frac{1-I}{I}$ follows the specification of Acemoglu and Zilibotti (2001) for tasks performed by skilled and unskilled workers.

[41] This is analogous to assuming that family labor and land are the fixed factors in production and there are decreasing returns to labor and capital.

ing profits net of the return to land. To tackle the second challenge, we exploit our detailed task data and adjust family working days at each stage with the days reported by the household head, who disproportionally engages in supervision activities, with 74% of households reporting the household head engaging in supervision.

6.3 Shadow Value of Family Labor

To compute the shadow value of family labor we exploit the optimality condition with respect to family engagement in the farm and the constant returns assumption on the production technology, i.e.

$$w_f = \alpha_f \frac{Y}{n_f^P + n_f^H + sn}$$

where $\alpha_f = 1 - \alpha^H - \alpha - \alpha_l$. That is, a fraction α_f of value added correspond to the payments to family labor. All variables in this condition are observable, except for family supervision effort, s. To discipline its value, we exploit the model's prediction for the optimal supervision time, i.e. proportional to hired labor, and the observed labor supply of family workers engaged in supervision at the preparation stage.[42]

6.4 Changes in Contracting Frictions

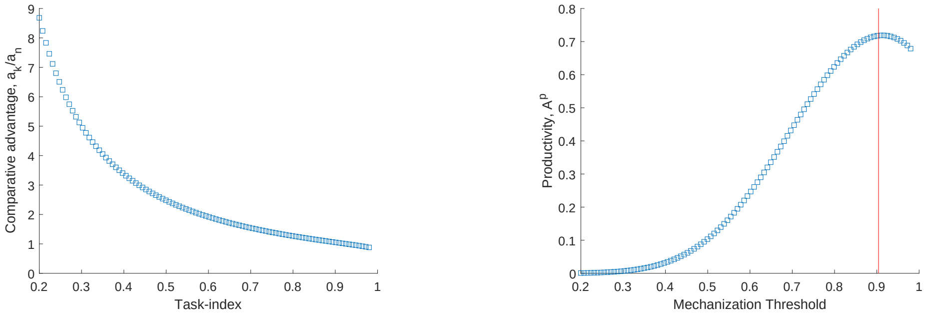
To identify possible changes in the contracting frictions in response to the subsidy, we exploit the optimal allocation of supervision labor, equation 4. Through the lens of the model, if the ratio of supervision labor to hired labor changes in response to the subsidy, so do supervision needs, ω.

$$\frac{d\ln(\omega)}{d\ln(r)} = \frac{d\ln(\frac{n_s^j}{n^j})}{d\ln(r)}$$

This elasticity is reported in Table C10.

[42]We could alternatively use information from the control group to estimate a linear relationship between family and non-family labor as in Foster and Rosenzweig (2017). We favour our approach because it allows us to directly link changes in the friction to the elasticity of the labor ratios from the experiment.

Figure 1: Calibrated profiles.



Panel (a) plots the calibrated profile for bias of technology of capital over labor in capital, $\frac{a_k(i)}{a_n(i)}$. Panel (b) plots implied productivity for different levels of the mechanization threshold in blue. In red we plot the mechanization threshold for the average farmer.

7 Quantifying Channels and Welfare

In this section we infer the threshold for mechanization for the mean farmer in our sample. Table 8 describes the parameterization of the model. Farm revenue and expenses are computed for the average farm in the control group. Revenues are net of intermediate input expenses because we only model value-added. The elasticities of revenue per acre, capital per acre and family labor are as reported in Section 4. Importantly, the shape of the bias of technology is calibrated to match the implied elasticity of total factor productivity to the subsidy, see figure 1. We calibrate the elasticity of the cost of capital to treatment using the differences in the elasticity of the cost of capital and the elasticity of the mechanization hours to treatment. This yields a decline in the cost of mechanization of 9p.p..

7.1 Returns to Capital

To identify mechanization thresholds, we need to construct an estimate of the land share in production, α_l. We compute the user cost of land 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 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. The share of family labor is computed as a residual from the share of capital, labor and

Table 8: Parameterization

	Parameter	Baseline		Source
A. Levels				
	$\frac{y}{l}$	26024		Control
	rk	2068		Control
	wn^P	2040		Control
	wn^H	15759		Control
	profits	6156		Table C15
	span of control	4.7		Table C10
B. Elasticities				
	$\epsilon_{\frac{y}{l}}$	0.0		Table C15
	$\epsilon_{\frac{k}{l}}$	0.101		Table 2
		Male	Female	
	$\epsilon_{\frac{n_f^P}{l}}$	-0.105	-0.1	Table 3
	$\epsilon_{\frac{n^P}{l}}$	0.0	0.0	Table 3
	$\epsilon_{\frac{n_f^H}{l}}$	-0.133	-0.1	Table 3
	$\epsilon_{\frac{n^H}{l}}$	0.0	-0.116	Table 3
C. Other parameters				
	β_1	2.32		calibrated jointly
	β_2	1.04		calibrated jointly
	$\epsilon_{r,treatment}$	-0.09		experimental design

Column (1) presents the benchmark parameterization while Column (2) presents the sources for the parameterization. Panel A. reports revenue and expenses for the mean of the control group in our sample. It also reports the ratio of supervision days to hired labor days for the control. Panel B. reports the relevant elasticities discussed in Section 4. Point estimates noisily estimated are assumed zero. Panel C. reports the jointly calibrated parameters describing the bias of technology between capital and labor, as described in Section 6.2; as well as the change in the cost of renting capital. See Appendix B.

land, and the assumption of constant returns. Table 9 presents these results.

At the mean, the share of capital in value added is 8% while the share of labor at the preparation stage is 1% (consistent with a relatively low labor engagement). At the harvest stage, the share of hired labor reaches 60%. The return to land is estimated at 2% and the remaining 28% is assigned to family labor. With this parameterization, we find that 90% of all mechanizable tasks are indeed performed by capital. This threshold implies a return to capital at the preparation stage is 8.8%, our main estimate.

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 capital barely increases to 90.41% (from

Table 9: Returns

αI	$\alpha(1-I)$	α_l	α_f^H	α^H	I	α
Baseline, frictionless capital markets						
8.0	0.8	2.2	28.4	60.5	0.90	8.8
Frictions, $MPK = r\tau$ for $\tau = 0.56$.						
14.1	1.5	2.2	21.6	60.5	0.90	15.5

This table presents estimates of the inputs shares (inp.p.) for different factors of production, as well as the identified threshold for mechanization I and the returns to capital at the preparation stage, α. First, returns are identified under the assumption of frictionless capital markets. Second, we consider the largest gap between the marginal product of capital and the cost of capital that is consistent with a shadow value of family labor that rationalizes households' engagement in agricultural activities, $\tau = 0.56$. These two alternative assumptions yield a lower and upper bound on the returns to capital.

90.4% at benchmark) and the return to capital remains at $\alpha = 8.8\%$. The reason is that the threshold is identified off of the elasticity of farm productivity to the subsidy which is not a function of the *levels* of the factor shares, see equation 10.

A key restriction to the identification of the threshold of capital as well as the capital share of output is the assumption that farmers operate in a frictionless capital market. Constraints that generate wedges between market prices and the marginal product of capital, including credit frictions, information frictions or relational contracts, would break this assumption.[43] To explore the impact of these intrinsically unobserved frictions on equilibrium allocations, we model a gap between the marginal product of capital and its price as $\tau \in (0, 1)$,

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

Hence, as $\tau \to 1$ the marginal product lines up with the market price, and as $\tau \to 0$ 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 capital through their effect on the share of tasks being mechanized. However, the share of capital is identified from changes in factor shares and allocations induced by the experiment, as well as the level of the capital-labor ratio

[43] From the point of view of the experimental design, the samples are balanced in terms of our index of credit constraints and therefore, the estimates of the elasticities are robust to differences in these constraints.

of the control group. Therefore, while the threshold is not affected by such a distortion, the mapping between capital expenses and the factor share is. When we include a gap between the market rental rate and the value of the marginal product of capital of 1.8 (equivalent to $\tau = 0.56$), the return to capital α raises to 15.5%. We calibrate τ so that shadow value of family labor on the farm equals average wages in other farms, as reported by the control group, i.e. ₹238. If instead we calibrate τ so that the shadow value of family labor on the farm equals the shadow value of the average hired worker in the farm, $\frac{w}{(1-s)}$ =₹244 we obtain a similar return, at $\alpha = 15\%$ (for a $\tau = 0.58$). We use the former estimate as the upper bound to the estimated returns.

7.2 Effects on Productivity

One of the predictions of our experiment is that revenue per acre increases in response to the subsidy in capital but not significantly. In this section we explore the channels affecting endogenous total factor productivity. In particular, we parameterize equation 7 using the estimates of the elasticities, the identified threshold and baseline expenses. To compute the size of different channels we also need measures of average mechanization, i.e. hours per acre for the control (which we estimate at 6.8 hours per acre at the mean), and family labor per acre for the control, as reported in Table 3.

Table 10 reports our findings for the relative strength of each channel explaining changes in revenue per acre. We find that the intensive mechanization effect (more capital) is stronger than the extensive mechanization effect (more tasks performed by capital). Because a large share of tasks are already mechanized at preparation for the control group, see Figure 1, the former effect is stronger than the latter. Finally, the labor replacement channel is positive at 7.4 p.p.. Hence, changes in productivity are accounted for the difference between the intensive mechanization channel and the labor replacement effect. Overall, we find that the elasticity of total factor productivity to treatment is 6.6pp.

If instead we compute the total factor productivity for the economy with a wedge in capital rental markets, the implied productivity improvement is 5 p.p. The lower productivity gain is explained by a lower magnitude of the labor replacement channel (1p.p. lower due to a lower residual share for family productive labor), and a higher intensive mechanization channel, directly linked to the wedge in the rental capital market.

Table 10: Productivity Decomposition, channels (percentage points)

Revenue per acre	Intensive mechanization	Extensive mechanization	Labor Replacement	Total	TFP
A. Benchmark, frictionless capital markets					
(1)	(2)	(3)	(4)	(5) -(2)+(3)+(4)	(6) (5)+(1)
0.0	0.8	0.01	7.4	6.6	6.6
B. Frictions in capital markets, $MPK = r\tau$ for $\tau = 0.56$.					
(1)	(2)	(3)	(4)	(5) -(2)+(3)+(4)	(6) (5)+(1)
0.0	1.4	0.01	6.4	5	5
C. Higher land share, $\alpha_l = 0.21$.					
(1)	(2)	(3)	(4)	(5) -(2)+(3)+(4)	(6) (5)+(1)
0.0	0.8	0.01	4.8	4.0	4.0

Each element of the table computes different channels through which a subsidy on mechanization affects revenue per acre, as characterized in equation 7. The elasticities to treatment and mean expenses for the control group are as described in Table 8 and input shares are reported in Table 9. The elasticity of total factor productivity is computed as a residual of the elasticity of revenue per worker, and all channels. Panel A. presents our benchmark results, Panel B. presents results when we allow for frictions in capital rental markets, and Panel C. presents results when we increase the share of land to 21% as in Adamopoulos and Restuccia (2014).

7.3 Family Compensation and Contracting Frictions

As we mention in Section 6.3, it is possible to back-up family wages from the residual share of value added and family engagement in the farm in all activities, including supervision:

$$w_f = \alpha_f \frac{Y}{n_f^P + n_f^H + sn}$$

We find that implied wages per day of family labor engagement in the farm is ₹313, below the average observed wages for our base employment group, i.e. male hired workers at the preparation stage, ₹372. The gap between their shadow value and the cost of labor (16%) is consistent with contracting frictions that tie family workers to their farm, modeled in Section 5.3.

How do these wages compare to other labor opportunities for farming households? Average daily wages in other farms are ₹238 consistent with no-significant movements in non-farm labor activities on average. Average daily wages in non-agricultural activities are ₹393.6, higher than the implied shadow value of family on the farm (with an implied gap of 20.4%). Notice that the cost of hired labor in the farm is $\frac{w}{(1-s)}$ =₹472, which is higher than family returns to working outside agriculture and may rationalize family engagement in farming.[44]

7.4 Welfare Effects From the Intervention

Table 11: Welfare

	Consumption-equivalent welfare	
	(a) γ_W	(b) γ_{W,n_l}
(1) Total	0.9%	1.5%
(2) Baseline	0.0%	0.0%
(3) More task-mechanized	-0.1%	-1.0%
(4) More task-mechanized, GE	17.1%	-6.7%
(5) Labor requirements, harvesting.	-17.8%	-9.2%
(6) Higher TFP	-4.5%	-0.6%
(7) Better supervision	-0.8%	1.0%
(8) Capital deepening	0.9%	1.5%

Column (a) displays consumption-equivalent welfare accounting for differences in leisure relative to the baseline as described in the text. Column (b) displays consumption-equivalent welfare when leisure is constant at its baseline level. The first row presents the overall effect of the intervention. Effects reported along rows two onwards are cumulative from top to bottom. Row (3) presents results when the set of tasks performed by the machine changes as predicted by the model but the effect on capital returns and optimal labor allocation in other stages (other than land-preparation) are not accounted. Row (4) includes all these additional effects. Row (5) shifts the productivity of labor in the other stages to match the decline in labor from the experimental results. Row (6) includes the endogenous shift in TFP as computed in Section 7.2. Row (7) includes the shift in supervision requirements as estimated in Section 6.4. Row (8) includes the shift in hours of mechanization from the experimental evidence.

We conclude the analysis of the implications of the experiment with a welfare calculation. In doing so, we calibrate the wedge in the marginal product of capital and the market rental cost of capital to target a shadow value of family labor equal to their outside option, i.e. the value of wages in non-agriculture. This is consistent with family labor engagement both in the farm and in nearby non-agricultural activities. Preferences are logarithmic and separable in consumption and leisure in each stage, $U(c^j, n_l^j) = \ln(c^j) + \ln(n_l^j)$. There are two periods that are relevant to the decisions of the household. Households discount future consumption at 1.5% over the three months window that the agricultural season lasts, consistently with an annualized interest rate of 6% (which we also used to compute the user cost of land). Let consumption in the baseline economy be c_b

[44] Wages for hired labor are computed for the base group.

and let leisure in the land-preparation stage and non-land preparation stage be n_{lb}^P and n_{lb}^H,respectively.[45]

Let us define the level of welfare of the households in our economy as

$$W(c, n_l^P, n_{l^H}) \equiv U(c, n_l^P) + \frac{1}{R}U(c, n_l^H) = \phi \ln(c) + \nu(n_l^P, n_l^H),$$

where $\phi = 1 + \frac{1}{R}$ and $\nu(n_l^P, n_l^H) \equiv \ln(n_l^P) + \frac{1}{R}\ln(n_l^H)$. We construct two measures of welfare. First, a measure of consumption-equivalent welfare, γ_W. That is, the percentage increase in consumption that we would have required for the average farmer to be indifferent between the economy with a reduction in the cost of mechanization and the baseline economy.

$$c_b(1+\gamma_W) = \phi e^{\ln(c)\phi + \nu(n_l^P, n_l^H) - \nu(n_{lb}^P, n_{lb}^H)}$$

In our problem, both consumption and leisure respond to the intervention. Therefore, we construct a second measure of consumption-equivalent welfare assuming that leisure remains at its baseline level, $\gamma_{W,nl}$.

$$c_b(1+\gamma_{W,nl}) = \phi e^{\ln(c)\phi}$$

The estimated consumption-equivalent welfare from the intervention is 0.9% over the season, as shown in Table 11. If we abstract from the change in leisure associated to the equilibrium response of labor to the decline in the cost of capital, the consumption-equivalent welfare is 1.5%. Relative to the baseline allocation, leisure falls at preparation to accommodate higher non-agricultural labor engagement, while leisure increases at harvesting in response to the lower overall employment needs (for both supervision and productive work). The first effect dominates, so the change in consumption needed for a farmer to be indifferent between the subsidy economy and the unsubsidized economy is higher when he adjusts labor supply (and leisure) than when he does not.

The intervention induces welfare gains through a variety of channels which our structural model allows us to disentangle. The intervention induces savings in labor in stages other than the one being mechanized. It also changes the set of tasks mechanized, with direct effects on labor demand at preparation. However, the shift in the mechanization threshold changes the return to capital

[45] Note that the optimal level of consumption is constant between land-preparation and non-land preparation.

(for a fixed level of capital services, i.e. αI), and it also increases the demand for labor in stages other than land-preparation because it makes inputs other than capital, more productive. The observed decline in labor in stages other than land preparation is consistent with technological savings in labor requirements which we summarize by $b(I)$. Higher TFP induces savings in family engagement in the farm and incentivizes those workers to take opportunities outside the farm.

In terms of welfare changes, not surprisingly, the largest contributors are the endogenous shift in the set of tasks being mechanized and its impact on the demand for other factors of production, as well as the productivity improvement. The second most important contributor to these changes is the reduction in supervision needs (contributing 3.7% in consumption-equivalent welfare). Capital deepening (on the extensive margin) contributed an additional 1.7% in consumption-equivalent welfare. [46]

7.5 Decomposing Labor Responses

The equilibrium of the model allows us to explore the strength of different channels for family labor supply decisions and hired labor demand decisions. To explore these changes, we solve the parameterized economy including each channel in isolation. We find that improvements in farming total factor productivity as well as the changes in inputs in response to the mechanization of tasks are the strongest contributors to the increase in labor supply in non-agriculture. A full description of the exercise can be found in the Online Appendix.

8 Conclusion

We provide the first causal estimates of the returns to mechanization. We find no statistically significant increases in output per acre on average, but our structural estimates of the shifts in productivity suggest improvements between 5 to 6.6p.p. over the season. This improvement is reflected in 1.5p.p higher welfare. A key contributor to these gains is the decline in supervision needs for family workers, which allows them to increase the span of control on the farm, and take opportunities in non-agriculture. We identify a key margin through which the returns to mechanization are realized, output standardization. Mechanization

[46] Importantly, we have abstracted from the cost of the intervention in assessing these gains. However, these costs are easily incorporated into the analysis by taxing farming households lump-sum by the size of the subsidy. Quantitatitavely, this effect is meager, less than 0.1p.p.

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.

We structurally bound the marginal returns to capital in land preparation at between 8.8% and 15.5%, depending on assumptions for the prevalence of frictions in capital rental markets. The measurement of the marginal returns to adoption of mechanized practices as well as their impact on productivity and labor are of first order relevance to understanding the effect of policies directed towards capital intensification in agriculture. When technology is embodied in large indivisible stocks, capital ownership may not be optimal for small production units. To the extent that 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 economic development.[47]

While the experimental design could have allowed mechanization impacts throughout the agricultural season, treatment effects on mechanization were concentrated at land preparation. Yet, mechanization of other stages of production is widespread in more developed economies and richer agricultural regions in India. Hence, we view our estimates as a lower bound to the marginal returns to mechanization in agriculture. Importantly, these returns as well as the effects on labor supply and demand are likely not invariant to the scale of operation. Our experimental elasticities could be an important input to future studies of the impact of land-consolidations and capital deepening for agricultural productivity and structural transformation.

[47]Related work in Caunedo et al. (2020) analyzes the impact of different arrangements for rental markets on service access and efficiency of the allocation.

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A Allocations

Preparation stage The optimality conditions for inputs across tasks are

$$p(i)a_n(i) = w + sw_f, \tag{12}$$

$$p(i)a_n(i) = w_f, \tag{13}$$

$$p(i)a_k(i) = r, \tag{14}$$

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

Optimality conditions for tasks

$$\alpha y^P = p(i)x(i)$$

The optimality conditions with respect to input intake are

$$\alpha(1-I)\frac{y}{n_f^P + n^P} = w_f, \tag{15}$$

$$\alpha(1-I)\frac{y}{n_f^P + n^P} = w + sw_f \text{ if } n^P > 0, \tag{16}$$

$$\alpha I \frac{y}{k} = r. \tag{17}$$

Harvesting stage

The optimality conditions with respect to input intake are

$$\alpha^H \frac{y}{n_f^H} = w_f, \tag{18}$$

$$\alpha^H \frac{y}{n^H} = w + sw_f. \tag{19}$$

B Mapping Between the Model and the Data

First we describe the construction of key model-variables from the available information in the control group.

- Value-Added: following the expenditure approach it equals profits, capital and labor expenses.

- Gross-Output: following the expenditure approach it equals Value-Added plus expenses in other intermediate inputs.

- Labor-Expenses: using control means, we construct a model consistent measures of labor expenses as the sum of the product between average wages and average working days per stage and gender.[48]

- Change in rental cost: we infer this change from the elasticity of capital expenses and mechanization hours to treatment. The elasticity of the implied cost of capital to treatment was 9pp.

- Labor: labor demand varies by gender, family vs. hired workers and stages. We transform labor intake using hired men at land preparation as the numeraire. Labor demand for other groups are adjusted by the relative average wages of that group to the numeraire, i.e. we construct a measure of full-time equivalent men hired workers.

- Productive and supervision family labor: we observe overall labor engagement for family members whose primary engagement in the farm is supervision. We substract their engagement from the overall days reported as family labor supply to the farm to construct a measure of family productive labor. The baseline results substract their engagement at the preparation stage.[49]

[48] Average expenses by stage as reported in Table C14 are slightly higher than the implied ones following our methodology.

[49] Our results are robust to alternative assignments (i.e. proportional to their engagement in preparation and other stages) and available upon request.

C Online Appendix

C.1 Labor Decisions

To illustrate how the farming household labor decision and his demand for hired labor change in response to mechanization we solve a simple version of the model. We parameterize the production technology as $Z(n_f^P + n^P)^\gamma$. The impact of mechanization can be illustrated through a change in the labor share, γ, and a change in productivity Z, as in the benchmark model. To express output as a function of labor decisions at the preparation stage only, we exploit the optimality conditions for farming labor at the preparation and harvesting stages. These conditions imply that family and non-family labor at the harvesting stage are linear functions of the labor input at preparation, i.e. $n_f^H = \frac{\alpha_f^H}{\alpha(1-I)}\left(n_f^P + n^P\right)$ and $n^H = \frac{\alpha^H}{\alpha(1-I)}\left(n_f^P + n^P\right)$. Therefore, γ is defined as $\gamma = \alpha(1-I) + \alpha_f^H + \alpha^H$. The level of productivity is $Z \equiv A^P k^{\alpha I} l^{\alpha_l} \left(\frac{\alpha_f^H}{\alpha(1-I)}\right)^{\alpha_f^H} \left(\frac{\alpha^H}{\alpha(1-I)}\right)^{\alpha^H}$.

The optimal time allocation by the household satisfies,

$$\frac{\partial \pi}{\partial n_f^P} \leq \frac{c}{n_l},$$

$$\frac{\partial \pi}{\partial n^P} \leq w + \frac{c}{n_l}\omega,$$

$$w_o \leq \frac{c}{n_l},$$

plus the budget constraint and the time constraint. The optimal allocation has different features depending on the relative wages and the intensity of the moral hazard problem as we explain below.

Case I: no outside family labor $n_f > 0$, $n_o = 0$, $n > 0$. This allocation requires that the value of the outside option, w_o, be larger than the effective cost of hired labor, $\frac{w}{1-\omega}$. Note that this might be the case, even when agricultural wages are below the non-agriculture ones $w < w_o$, because of the contracting frictions, summarized by ω.

$$n_f = \left(\frac{\gamma Z}{\frac{w}{1-\omega}}\right)^{\frac{1}{1-\gamma}}$$

Whether hired labor is positive or not depends on the marginal product of labor, which scales of farming productivity, and the size of the family through the available working time, $\bar{n}$.

Case II: no hired labor $n_f > 0$,$n_o \geq 0$, $n = 0$. Importantly, when there is no hired labor engaged in production, the relative outside option for family labor is the wage in the non-agricultural sector. In an optimum with no hired labor, family labor on the farm satisfies,

$$n_f = \left(\frac{\gamma Z}{w_o}\right)^{\frac{1}{1-\gamma}}$$

If the wage in non-agriculture is relatively low, family labor only works in the farm.

Case III: no hired labor $n_f \geq 0$,$n_o > 0$, $n > 0$. When farming productivity, or the share of labor in farming is relatively high, the farmer hires outside workers. If in addition the farmer decides to work outside the farm, the equilibrium requires that the shadow value of hired labor be the same as the opportunity cost of family labor, which in this case is pin down by the outside option. In this case, there is continuum of combinations of family and hired labor that solve the equilibrium allocation, because the farmer is indifferent between hiring workers and their outside option. This case arises only when the outside option is relatively high, and therefore the farmer decides not to put its own labor on the farm (except through supervision time), $n_f = 0$.

If the wage in non-agriculture is relatively low, then the farmer chooses to work in the farm, as in Case I.

C.2 Decomposing Labor Responses

To explore these changes, we solve the parameterized economy including each channel in isolation. Table C1 reports the cumulative effect of each channel for labor decisions. The parameterized model generates 52% of the family labor supply elasticity in farming at preparation (-4.2p.p. in the model versus -8p.p. on average across genders in the experiment), and 63% of the decline in family labor supply in farming at harvesting (-8.2p.p. in the model versus -13p.p. on average across genders in the experiment).

In terms of the contribution of different channels for labor supply, we first change the mechanization threshold at preparation imposing no changes in optimal labor demand in other stages of production. Labor demand for hired labor falls, as well as labor demand for supervision activities. Labor supply in non-agriculture declines consistently with the income effect of the improvement in farming productivity. When we allow the labor allocation in other stages to respond to the subsidy we observe a strong response in farming labor across processes as well as an increase in non-agricultural engagement. If we introduce the change in labor requirements that are consistent with the behavioral decline in hired labor at harvesting we observe declines in labor at harvesting for both family and hired labor and a switch in equilibrium, towards one where farmers rely solely on their own labor supply at land preparation. This increase in family labor at preparation induces a decline in non-agricultural engagement. Then, we consider the effect of the improvement in total factor productivity driven by the bias of technology. Relative to the baseline economy, higher total factor productivity induces a decline in labor demand for both hired and family labor, and a decline in non-farm labor. If in addition we improve the technology for supervision (lower s) the labor demand increases, particularly so for hired labor at preparation. Finally, once we account for higher mechanization hours (i.e. the intensive mechanization channel), labor at land preparation is predicted to increase slightly, family labor to fall across stages and non-agricultural labor engagement to increase.[50]

The isolation of each of these channels highlights their role for labor allocation within and outside the farm. It also emphasizes the role of equilibrium responses as well as labor market frictions for the direction and size of the experimental labor responses.

[50] The impact on hired labor at harvesting is targeted through the change in requirements $b(I)$.

Table C1: Labor Responses

	Land preparation		Non land preparation		Non ag. labor
	(a) Hired	(b) Family	(c) Hired	(d)Family	(e)
	n^p	$n_f^p + sn$	n^H	$n_f^H + sn$	n_o
(1) Total	3.3%	-4.2%	-6%	-8.2%	0.8%
(2) Baseline	0.0%	0.0%	0%	0.0%	0.0%
(3) More tasks mechanized	-0.3%	-0.3%	9%	9.2%	-0.1%
(4) More tasks mechanized, GE	123.7%	123.6%	145%	145.1%	8.4%
(5) Labor requirements, harvesting.	.	150.8%	-52%	-51.6%	-15.4%
(6) Higher TFP	-17.3%	-17.3%	-25%	-24.8%	-3.4%
(7) Better supervision	-4.2%	-11.1%	-13%	-14.8%	-0.4%
(8) Capital deepening	3.3%	-4.2%	-6%	-8.2%	0.8%

Column (a) displays changes in hired employment and column (b) displays changes in family labor engagement at land preparation. Columns (c-d) display changes in hired employment and family labor engagement in the farm at stages other than land-preparation. Column (e) display family labor engagement outside the farm. The first row presents the overall effect of the intervention. Effects reported along rows two onwards are cumulative from top to bottom. Row (3) presents results when the set of tasks performed by the machine changes as predicted by the model but the effect on capital returns and optimal labor allocation in other stages (other than land-preparation) are not accounted for. Row (4) includes all these additional effects. Row (5) shifts the productivity of labor in the other stages to match the decline in labor from the experimental results. Row (6) includes the endogenous shift in TFP as computed in Section 7.2. Row (7) includes the shift in supervision requirements as estimated in Section 6.4. Row (8) includes the shift in hours of mechanization from the experimental evidence.

C.3 Tables

Table C2: Survey Binary Treatment Effects

	(1) 1(Surveyed In Person)	(2) 1(In-Person/Phone Survey)
1(Cash and Mechanization)	-0.00363	0.00245
	(0.0126)	(0.00916)
1(Mechanization)	0.0470****	0.0124
	(0.0128)	(0.00835)
Control Mean	0.750	0.920
Observations	7173	7173

Standard errors clustered at the village-level in parentheses.

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

The dependent variable in Column 1 is a binary variable that is 1 if the farmer was administered the endline survey in person. The dependent variable in Column 2 is a binary variable that is 1 if the farmer was administered the endline survey in person or on the phone.

Table C3: 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 C4: Balance Table

	(1)
Area Cultivated	0.0703
	(0.113)
1(Matched to Platform)	0.000240
	(0.0109)
IHS(Mechanization Index)	0.0126
	(0.0261)
Household Size	-0.0140
	(0.0556)
1(Credit Constrained)	0.00986
	(0.00761)
1(Household Head is Male)	-0.0116
	(0.00961)
1(SC/ST Household)	-0.00141
	(0.0163)
Log (Male Wage)	-0.00620
	(0.0288)
Log (Female Wage)	0.0195
	(0.0239)
Log(Nonagricultural Income)	-0.00642
	(0.132)
Log(Revenue per acre)	-0.0758
	(0.131)
Number of Family Males Working on the Farm	0.0339*
	(0.0196)
Number of Family Females Working on the Farm	-0.00560
	(0.0177)
Number of Hired Males Working on the Farm	0.335
	(0.205)
Number of Hired Females Working on the Farm	-0.1035
	(0.347)
Log (Span of Control: All Hired Workers to Male Family Workers)	0.0224
	(0.0255)
Number of Specialized Tasks: Family Males	-0.0371
	(0.045)
Number of Specialized Tasks: Hired Males	0.0567*
	(0.0281)
Number of Specialized Tasks: Family Female	-0.0144
	(0.018)
Number of Specialized Tasks: Hired Female	0.0257
	(0.024)
1(Own Any Equipment)	0.0176
	(0.0118)
Joint F-Stat	**0.29**
Observations	7235

Standard errors clustered at the village-level in parentheses

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

Table C5: Comparison of Census Sample with Intervention Sample

	Intervention Sample		Census Sample	
	Mean	SD	Mean	SD
Land holdings (Acres)	3.37	2.8	3.78	4.8
Agricultural Revenue (000s)	46.7	83.01	48.2	74.07
1(Paddy)	0.19	0.40	0.20	.42
1(Cotton)	0.20	0.40	0.23	.42
1(Maize)	0.13	0.34	0.17	0.38
Household Size	3.5	1.42	4.8	2.3

The table presents summary statistics for land, agricultural revenue, and binaries for growing three of the most common crops, all for the 2018 season.

Table C6: Take-Up: Direct and Spillover Effects

	(1)	(2)	(3)	(4)
	1(Matched to Platform)			
1(Mechanization)	0.324****	0.353****	0.329****	0.357****
	(0.0194)	(0.0208)	(0.0205)	(0.0223)
1(Spillover)	0.0250	0.0250	0.0266*	0.0266*
	(0.0159)	(0.0159)	(0.0151)	(0.0151)
1(Cash and Mechanization)		-0.0614****		-0.0596****
		(0.0158)		(0.0171)
EL Survey			X	X
Observations	7202	7161	5530	5492

Standard errors in parentheses. Clustering is at the village-level.

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

The dependent variable takes the value 1 if a farmer's phone number in the survey data could be matched to the mechanization rental platform data, and 0 otherwise.

1(Spillover) is a binary variable that takes the value 1 for control farmers in treated villages, and 0 otherwise.

Table C7: Mechanization Index Treatment Effects by Voucher

	(1) IHS (Mechanization Index)
1050 Subsidy	-0.00194
	(0.0857)
1050 Subsidy, 1050 Cash	-0.0110
	(0.0709)
2100 Subsidy	0.114**
	(0.0474)
2100 Subsidy, 1050 Cash	0.0376
	(0.0440)
1750 Subsidy	0.169**
	(0.0819)
1750 Subsidy, 1750 Cash	0.153**
	(0.0715)
3500 Subsidy	0.0775
	(0.0476)
3500 Subsidy, 1750 Cash	0.130*
	(0.0675)
1(Large Farmer)	0.458****
	(0.0337)
Control Mean	-0.0500
Observations	4989
P-Value of Testing	
1050 Subsidy=1750 Subsidy	0.136
1050 Subsidy, 1050 Cash=1750 Subsidy, 1750 Cash	0.0708*
2100 Subsidy=3500 Subsidy	0.543
2100 Subsidy, 1050 Cash=3500 Subsidy, 1750 Cash	0.212

Standard errors clustered at the village-level in parentheses.

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

The dependent variable is the inverse hyperbolic sine of the mechanization index. The index is constructed by standardizing all implement-wise hours, summing them, and dividing by area cultivated.

Table C8: Mechanization Index Treatment Effects For Land Preparation

	(1)	(2)	(3)	(4)
	IHS(Mechanization Index)		Change in IHS(Mechanization Index)	
1(Mechanization)	0.102***	0.0966**	0.0686	0.0549
	(0.0318)	(0.0387)	(0.0415)	(0.0488)
1(Cash and Mechanization)		0.0120		0.0303
		(0.0378)		(0.0471)
Control Mean	-0.0500	-0.0500	-0.0300	-0.0300
Observations	5535	5535	5465	5465

Standard errors clustered at the village-level in parentheses.

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

The dependent variable is the inverse hyperbolic sine of the mechanization index. The index is constructed by standardizing all implement-wise hours, summing them, and dividing by area cultivated.

Table C9: 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

A task is considered to be performed by a particular labor type if it was listed as being performed first in the profile of tasks listed for that labor type by the household.

Table C10: Span of Control With Worker Days

	(1)	(2)	(3)	(4)
	Span of Control		IHS(Span of Control)	
1(Mechanization)	0.512**	0.506**	0.0670**	0.0775**
	(0.240)	(0.249)	(0.0302)	(0.0362)
1(Cash and Mechanization)		0.00765		-0.0260
		(0.308)		(0.0417)
Control Mean Levels	4.710	4.710	4.710	4.710
Observations	3935	3907	3935	3907

Standard errors clustered at the village-level in parentheses.

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

The span of control is defined as the total number of days per acre of hired labor, divided by the number of days worked by household members that report supervision as one of their tasks.

Table C11: Binary for Labor Use: Treatment Effects

	Land preparation			
	(1)	(2)	(3)	(4)
	Family Male	Hired Male	Family Female	Hired Female
1(Mechanization)	-0.0130	0.0250*	-0.00306	0.0110
	(0.00990)	(0.0140)	(0.0149)	(0.0116)
1(Cash and Mechanization)	0.00230	-0.0101	0.00171	-0.0248**
	(0.0129)	(0.0170)	(0.0189)	(0.0119)
Control Mean Levels	0.940	0.690	0.450	0.230
Observations	5535	5535	5535	5535
	Other stages			
	(1)	(2)	(3)	(4)
	Family Male	Hired Male	Family Female	Hired Female
1(Mechanization)	-0.00830	0.0119	-0.0144	-0.00464
	(0.0137)	(0.0100)	(0.0141)	(0.00859)
1(Cash and Mechanization)	0.00641	-0.00748	-0.0111	0.0164*
	(0.0141)	(0.0140)	(0.0176)	(0.00882)
Control Mean Levels	0.820	0.860	0.760	0.930
Observations	5525	5533	5526	5531

Standard errors clustered at the village-level in parentheses.

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

Panel 1 reports binary variables for hiring different types of labor over the land preparation stage.

Panel 2 reports binary variables for hiring different types of labor over all stages except land preparation.

Table C12: Number of Workers During: Treatment Effects

	Land preparation			
	(1)	(2)	(3)	(4)
	Family Male	Hired Male	Family Female	Hired Female
1(Mechanization)	-0.0859****	-0.0523**	-0.0320***	-0.0160
	(0.0191)	(0.0252)	(0.0119)	(0.0156)
1(Cash and Mechanization)	0.0294*	-0.0224	0.0141	-0.0209
	(0.0172)	(0.0282)	(0.0134)	(0.0161)
Control Mean Levels	0.740	1.310	0.280	0.350
Observations	5502	5511	5484	5486
	Other stages			
	(1)	(2)	(3)	(4)
	Family Male	Hired Male	Family Female	Hired Female
1(Mechanization)	-0.119****	-0.121****	-0.109****	-0.131****
	(0.0297)	(0.0343)	(0.0274)	(0.0335)
1(Cash and Mechanization)	0.0314	0.0297	0.00158	0.0863**
	(0.0295)	(0.0463)	(0.0304)	(0.0400)
Control Mean Levels	2.190	5.390	1.700	8.330
Observations	5525	5533	5526	5531

Standard errors clustered at the village-level in parentheses.

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

The dependent variables are the inverse hyperbolic sine of the number of workers per acre.

Table C13: Wages: Treatment Effects

	Entire Season			
	(1)	(2)	(3)	(4)
	IHS(Male Wage)	Male Wage	IHS(Female Wage)	Female Wage
1(Mechanization)	0.0307	0.141	0.0363**	2.413
	(0.0205)	(2.533)	(0.0181)	(2.087)
1(Cash and Mechanization)	-0.0221	-1.903	-0.0204	-2.183
	(0.0195)	(2.662)	(0.0170)	(2.220)
Control Mean Levels	355.6	355.6	210.2	210.2
Observations	4791	4791	4843	4843
	Land Preparation			
	(1)	(2)	(3)	(4)
	IHS(Male Wage)	Male Wage	IHS(Female Wage)	Female Wage
1(Mechanization)	-0.00359	1.173	-0.0472	2.461
	(0.0328)	(5.532)	(0.0678)	(3.883)
1(Cash and Mechanization)	0.0389	-0.675	0.0678	2.694
	(0.0352)	(5.828)	(0.0842)	(4.126)
Control Mean Levels	371.8	371.8	212.3	212.3
Observations	3888	3888	1697	1697
	Non-Land Preparation			
	(1)	(2)	(3)	(4)
	IHS(Male Wage)	Male Wage	IHS(Female Wage)	Female Wage
1(Mechanization)	-0.0156	-1.330	0.00387	2.379
	(0.0433)	(3.136)	(0.0366)	(2.316)
1(Cash and Mechanization)	0.00986	-1.523	-0.0319	-2.913
	(0.0468)	(3.210)	(0.0398)	(2.624)
Control Mean Levels	350.6	350.6	208.8	208.8
Observations	4539	4539	4806	4806

Standard errors clustered at the village-level in parentheses.

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

Panel 1 reports wages for male and female hired labor averaged across all production stages.

Panel 2 reports wages for male and female hired labor for land preparation only.

Panel 1 reports wages for male and female hired labor averaged across all production stages except land preparation.

Table C14: Labor and Capital Expenditure Per Acre

	(1) Mechanization	(2) Non-Land Preparation Labor	(3) Land Preparation Labor
1(Mechanization)	-0.0410	-0.119	-0.118
	(0.117)	(0.0774)	(0.106)
1(Cash and Mechanization)	0.155	0.0469	0.0249
	(0.112)	(0.0843)	(0.112)
Control Mean	2068.5	16935.5	2783.5
Observations	5444	5056	3963

Standard errors clustered at the village-level in parentheses.

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

Mechanization is the mechanization expenses in ₹per acre (only land preparation is mechanized).

Non-Land Preparation Labor is expenses for hired labor in ₹per acre in all stages except land preparation.

Land Preparation Labor is expenses for hired labor in ₹per acre during land preparation.

Table C15: Output Per Acre: Treatment Effects

	(1) 1(Output Sold)	(2) Proportion Sold	(3) IHS(Revenue/Acre)	(4) IHS(Profit/Acre)
1(Mechanization)	-0.00903	-0.0138	0.0732	-0.136
	(0.0118)	(0.0117)	(0.0688)	(0.247)
1(Cash and Mechanization)	0.0202	0.00444	-0.143*	0.513*
	(0.0133)	(0.0157)	(0.0815)	(0.282)
Control Mean Levels	0.840	0.79	42611.4	6156.3
Observations	5497	5075	5076	5459

Standard errors clustered at the village-level in parentheses.

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

1(Output Sold) is a binary variable that takes the value 1 if the farmer reported selling input, and 0 otherwise. Proportion Sold is the proportion of output sold. IHS(Profit/Acre) is the money left over from farming reported by the farmer. IHS(Revenue/Acre) is the sum of expenses and profits.

Table C16: Output and Revenue Per Acre With Consistently Non-Missing Data: Treatment Effects

	(1) 1(Output Sold)	(2) Proportion Sold	(3) IHS(Revenue/Acre)	(4) IHS(Profit/Acre)
1(Mechanization)	-0.00313	-0.00803	0.0174	-0.0812
	(0.0102)	(0.0119)	(0.0629)	(0.235)
1(Cash and Mechanization)	0.00250	0.00218	-0.105	0.416
	(0.0133)	(0.0159)	(0.0714)	(0.301)
Control Mean Levels	0.90	0.79	43993.4	6986.6
Observations	4843	4763	4843	4843

Standard errors clustered at the village-level in parentheses.

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

1(Output Sold) is a binary variable that takes the value 1 if the farmer reported selling input, and 0 otherwise. Proportion Sold is the proportion of output sold. IHS(Profit/Acre) is the money left over from farming reported by the farmer. IHS(Revenue/Acre) is the sum of expenses and profits.