NBER WORKING PAPER SERIES

MECHANIZING AGRICULTURE

Julieta Caunedo
Namrata Kala

Working Paper 29061
http://www.nber.org/papers/w29061

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2021, Revised January 2022

The authors thank the Agricultural Technology Adoption Initiative (ATAI), MIT Sloan School of Management, Institute of Social Sciences at Cornell University, International Growth Center (IGC), and Private Enterprise Development in Low-Income Countries (PEDL) for their generous financial support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Mechanizing Agriculture
Julieta Caunedo and Namrata Kala
NBER Working Paper No. 29061
July 2021, Revised January 2022
JEL No. D13,D2,O13,O53,Q0

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.

Julieta Caunedo
452 Uris Hall
Cornell University
Ithaca, NY 14853
jdc364@cornell.edu

Namrata Kala
MIT Sloan School of Management
100 Main Street, E62-517
Cambridge, MA 02142
and CEPR
and also NBER
kala@mit.edu

A online appendix is available at http://www.nber.org/data-appendix/w29061

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 to supervise 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 downstream activities 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 farming enterprises. The impact of mechanization on farmers' labor supply and span of control are novel channels for the transformative role of capital intensification of labor intensive activities. Studying this link using observational data is challenging due to the plausible correlation between farmers unobservable characteristics, e.g. managerial ability, adoption of mechanized practices and endowments. 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

[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 land-holdings in low and lower middle income countries, as reported by Graeub et al. (2016) based on FAO's World Census of Agriculture.

[2]There is an extensive literature on this topic, including, but not limited to, Baumol (1967), Timmer (1988), Kongsamut et al. (2001) and Ngai and Pissarides (2007). Gollin et al. (2002) estimates that 54% of the growth in GDP-per-capita across countries between 1960 and 1990s is due to growth in productivity within agriculture alone.

of the value of the vouchers in the form of a cash transfer. Available implements for rental include tractors, and implements such as rotavators, 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 our own 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 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 —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 downstream, unmechanized stages. At the same time, savings in worked days are different for hired and family labor: while family labor is released throughout the season and irrespective of gender, displacement for hired labor is concentrated amongst female workers, and outside the land preparation stages.

We investigate the mechanisms for the differential effects on labor types using detailed data on task specialization, at the household and individual level. First, we document substantial task specialization across family vs. hired labor, with nearly 90% of households reporting supervision being done by family male labor, while only about 3% of households reporting hired male labor engaging in supervision. This finding 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 6.4 p.p. in response to the subsidy. Deep and multiple rounds of tillage during land preparation both lowers the prevalence of weeds (Monaco et al., 2002; Jorgensen, 2018), as well as ensures that planting happens in consistent rows, so that subsequent operations are easier to monitor. This effect contributes to the decline in female labor engagement in downstream activities because these workers largely specialize in weeding and harvest. At the same time, deep tillage is known to improve the properties of the soil. While we find positive effects on revenues, these are noisily estimated. Finally, households' non-farm income increases by 3.6%, consistent with shifts in farmers labor supply towards non-agriculture. This effect is driven by households already engaged in non-farm activities at baseline.

We build a structural model of farming with heterogeneous land holdings, time endowment and supervision ability to isolate and quantify the welfare effects of the intervention, and the mechanisms for this effect. Farming is a multi-stage production technology where land preparation can be performed with machines or with labor, as in a model of task-replacement (Acemoglu and Autor, 2011). The main innovation of our model relative to these prior models is that decisions to adopt mechanized practices depend on the shadow value of the manager's time. The reason is that moral hazard in hired labor requires family effort for worker supervision and that effort raises the shadow cost of hired labor. Hence, production decisions and the farmers' consumption and labor supply decisions are non-separable. We use the reduced form estimates from the experiment and the structural predictions to calibrate the model. Then, we use identification restrictions from the model to 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 17% per season under the assumption of frictionless rental markets, and can be closer to 15% when we allow for frictions in these markets. The model also shows that the shadow value of family labor is 14.5% below their outside option, a gap that is consistent with contracting frictions that tie family workers to the operation of the farm. While the model is calibrated for the average farmer, disparities in land holdings, time endowments, and supervision ability are enough for it to endogenously generate the observed heterogeneity in household participation in non-agriculture, and in the market for hired labor at land-preparation.

We further exploit the structure of the model to rationalize the null effect on output per acre that we find experimentally, and the substantial decline in labor engagement outside land-preparation. The residual (and endogenous) productivity improvement that is consistent with the reduced form responses in employment, capital and value-added is 5.5% per season. Finally, we assess farmers' welfare from the intervention. Income changes are not sufficient to assess welfare because the intervention shifts households' incentives to work in non-agriculture

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

and the optimal leisure allocation across all stages of production. Furthermore, these shifts may vary given farmers' baseline engagement in these markets. We construct a measure of consumption-equivalent welfare and find that the intervention raised welfare by 5.5% when we abstract from shifts in labor supply, and that those gains increase to 12% when we include them. The main contributor to the welfare gains from labor supply changes is the improvement in the span of control (i.e. lower incidence of supervision needs) and the main contributor to consumption gains are the changes in total factor productivity.

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 for labor and productivity.[4] Importantly, we provide and quantify the role of output standardization associated with mechanized practices. Output standardization is valuable in environments with moral hazard problems, where family/managers' 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.[5] Our findings provide direct evidence for theories of disparities in operation sizes between poor and rich countries that include contracting frictions, as in Bloom and Van Reenen (2010) and Akcigit et al. (2020).

Second, our paper contributes to the literature that causally estimates 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 from capital alone for small farmers in Ghana. We estimate the returns to large mechanized equipment via rental markets, since small farm sizes make ownership of these implements

[4] 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).

[5] 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.

not cost-effective.[6] 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.[7] The point estimate of between 15.5% and 17% is higher than the estimate in Hayami and Ruttan (1971) for poor economies (10%), although arguably theirs is a measure of the capital share in output, which we find is 8.8% in our control group. The quantitative assessment through the structural model is akin to Buera et al. (2020), who use a general equilibrium model to interpret the effect of micro-finance programs.

Third, we document the impact of mechanization for labor reallocation away from agriculture into non-agriculture. There is an extensive (and mostly theoretical) literature on the role of capital deepening for structural change, including Acemoglu and Guerrieri (2008) and Alvarez-Cuadrado et al. (2017), although quantitative measures remain elusive.[8] The role of capital intensification for agricultural productivity has been studied in Caunedo and Keller (2021) 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, namely, 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.[9] Farmers in this region, like in most developing countries, are engaged in smallholder agriculture. The median land cultivated is 2 acres (the median is 3.3 acres), and the most common crops are paddy (rice), cotton, and maize. Most

[6]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).

[7]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).

[8]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.

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

farmers engage in rental markets: over 92% of the control group reported renting some equipment in the endline survey. The only production stage that is mechanized at baseline is the most upstream production stage, land preparation, with less than 2% of households reporting mechanization in a downstream stage. Farmers can rent equipment from other farmers in the same village (informally), or use custom hiring centers (CHC), which our implementation partner has established across the state (the formal rental market). For the latter, the farmer places a rental order using a phone number and receives the equipment with a driver.

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 until the requisite sample size was reached in a village. 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 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. In practice, farmers redeemed most of the subsidy they were given.

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, 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 with 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. Small farmers (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.[10] 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 A3.

Villages were either assigned to the high intensity arm (70 villages), low intensity arm (70 villages), or the control group (60 villages). The randomized intensity was to allow us to test for the presence of spillovers in mechanization use (to control farmers in treatment villages). In practice, these are very small and not economically important in our setting. 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 surveyed farmers about land-holdings, baseline levels of assets and savings, agricultural input use, and

[10]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.

agricultural income. In addition, we collected detailed data on labor use and wages by gender and the extent to which 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 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 A1, and is balanced across treatment groups, though there is a small difference in the probability of being surveyed in person.[11]

[11] 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.

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.

Table A4 shows the most commonly rented implements by the control group, as well as those most commonly rented from the CHCs in non-subsidized transactions. In both instances, land preparation implements, namely, cultivators, rotavators, and mechanical ploughs are most commonly rented. These are also implements with the largest inventory at the CHCs.[12]

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 A2 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:

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

where y_i is the outcome of interest for farmer i, and $\mathbb{1}[\text{Mechanization Voucher}_i]$ is a binary variable that takes the value 1 if the farmer received a subsidy voucher for mechanization rental, and is 0 otherwise. $\mathbb{1}[\text{Partial Mechanization Voucher in Cash}_i]$ 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. 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

[12] While a smaller number of other implements, such as knapsack sprayers, harvesters etc. are available, each such implement accounts for less than 5% of transactions.

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.[13]

Since we are unable to reject that vouchers of different amounts had statistically different effects (see Online Appendix), all voucher subsidy treatments were pooled 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.[14] 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 6p.p.). On average, treatment households received about ₹2418 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 the available subsidy, and do not add in additional funds of their own.

[13] 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.

[14] 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.

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 A5 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 and noisily estimated, indicating that spillover effects were extremely small to nonexistent. Given this, we pool all control farmers for all analysis, and include village-fixed effects in the estimation.[15]

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 for different stages of production. All implement-wise hours are standardized (by subtracting the mean and dividing by the standard deviation of the control group), 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. 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 show effects on the index in levels (winsorised at the 1st and 99th percentile) as well as on the inverse hyperbolic

[15]While the intervention could potentially have decreased prices in the informal market, in practice it was too small an intervention to do so. Of the farmers in the sample, about 278 rented out equipment in the informal market. Of these, only 3% reported decreasing prices over the season, with another 76% reporting that they did not change their prices at all.

sine (IHS) transformation on the index to dampen the effect of outliers.

Results are presented in Table 2.[16] The offer of a rental voucher increases mechanization by about 0.12 to 0.15 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)	(2)	(3)	(4)
	IHS (Mechanization Index)		Mechanization Index (Levels)	
1(Mechanization)	0.135****	0.159****	0.121***	0.141***
	(0.0356)	(0.0406)	(0.0374)	(0.0428)
1(Cash and Mechanization)		-0.0523		-0.0432
		(0.0374)		(0.0376)
Control Mean	-0.0500	-0.0500	0	0
Observations	4989	4989	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 in the first two columns is the inverse hyperbolic sine of the mechanization index.
The dependent variable in the third and fourth columns is the winsorised mechanization index in levels.
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 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 for family vs. non-family workers.

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

[16] While we report results for total mechanization hours, these should be interpreted as changes to land preparation mechanization. Table A6 presents treatment effects for land preparation only, and shows very similar treatment effects to considering overall mechanization.

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.[17]

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

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

Table 3: Labor Use Per Acre: Treatment Effects

	Family Male	Hired Male	Family Female	Hired Female
Entire Season				
	(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.

tasks-listed-first for each type of labor.[18] Table 4 shows that tasks performed by different types of labor vary substantially. In the online appendix we show results with the tasks-listed-first instead of tasks-ever-listed.The allocation of tasks across labor groups 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

[18]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.

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, since family labor has low or no moral hazard problems, for labor demand decisions. 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).

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
16	Other	1.33	2.62	3.49	1.78

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.[19] We use this data to

[19] 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.

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.[20] 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 households members that reported 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 A7 shows results for the number of worker days, and shows that treatment increases the number of hired labor days per supervising household member days by 0.5. The effect of mechanization on the span of control operates through two channels. First, if family labor is held fixed, any labor-saving technology would reduce the ratio of hired labor to family labor, i.e. 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. Arguably, the greatest risks for labor shirking and its effect on crop damage, likely occur during weeding, pest control, irrigation and sometimes even harvesting. How is that mechanization at land-preparation helps in this regard? 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, to output standardization. An alternative effect of mechanization is that it induces labor savings by reducing the probability that the farmer may need to resow a field due to poor initial preparation, lowering the demand for overall labor. This channel implies that there should be labor reductions at the preparation stage, for which we find weaker evidence.

4.4 Returns on the Subsidy

Before estimating the structural model to quantify welfare effects, it is useful to compute the monetary returns to the intervention. These returns stem from changes in farm profitability (either by an increase in revenue or a decline in

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

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.

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.[21] Since revenues are measured conditional on selling output, we test whether the probability of selling output as well as the proportion of output sold in the market are impacted by treatment and show this is not the case (see Table A8). 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.[22] Results for revenue and profit per acre are presented in Table A9. 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

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

[22] We also test the effect treatment on self-reported market revenues and yields, and we find no effect.

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 measure the returns on the subsidy, we compute additional revenue and savings in farming expenses net of additional capital expenses as a share of the average subsidy allocated to farmers, ₹2418 (computed using the voucher distribution in the sample). We find evidence of savings in intermediate inputs (a decline of 13% on average per acre) and an increase in capital expenses from CHCs, but only noisily estimated savings in labor and additional revenue which we omit (see Table A10). We estimate a return on the subsidy of 64% 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 on the farm by reallocating time towards nonagricultural work, 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-agriculture sources, non-agriculture income increases, and the effect is statistically and economically significant – a point estimate of 40%– if changes in non-agriculture income are considered.

Table 7: Non-Agriculture Income: Treatment Effects

	(1) 1(Any non-agriculture Income)	(2) IHS(non-agriculture Income)	(3) Change in IHS (non-agriculture 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-agriculture Income) is a binary variable that is 1 if the household reported income from non-agriculture sources, and 0 otherwise. IHS(Nonagricultural income) is the inverse hyperbolic sine of the level of household income from nonagricultural sources.

4.6 Interpreting the RCT.

A textbook interpretation of a voucher subsidy is that it induces a parallel shift in the farmer's isocost i.e. a pure income effect. Prima-facie, this effect is inconsistent with the reduced form estimates. The reason is that a pure income effect would have induced higher demand for both labor and capital, i.e. a standard scale effect when the marginal product of each of the inputs is positive and relative prices (at the margin) do not change. Instead, we document declines in the usage of labor (a displacement effect), including in stages not being mechanized. The subsidy we implemented entails a non-linear movement in the cost of renting services, with the equipment-hours equivalent of the subsidy amount priced at zero, and the remaining hours priced at the market rental rate. The observed higher capital-labor ratios are consistent with either a change in the relative cost of capital to labor, or a shift in technology altogether i.e. non-parallel shifts in iso-profit curve.Another thing worth noting is that the intervention does not seem to have induced a shift in new technology adoption– in particular, the probability of take-up of the vouchers is not higher amongst farmers who reported not renting any implements in the baseline (20% of the baseline sample).[23]

[23] The coefficient on the interaction between the voucher treatment dummy and the dummy variable for whether the farmer reported renting any implements in the baseline is 0.03, with

5 A Model of Mechanization and Farmers' Labor Supply.

Next, we present a model to interpret the average effects of the experiment, to account for the magnitude of different economic channels driving the observed results and to assess welfare from the intervention. Therefore, the model is an accounting tool that, in combination with our experimental design, allows us to identify key parameters of interest for future studies of the impact of subsidies at scale, including the returns to capital, the shadow value of unpaid family labor and importantly, the friction associated with workers' moral hazard. The model also highlights that welfare gains from the mechanization of production depend on the farmers' engagement on the farm (for supervision or productive purposes), the farmers outside option (i.e. non-agriculture) and their ability to manage workers in the field, through the incidence of the moral hazard friction.[24]

The economy is populated by a continuum of farming households that are heterogeneous in their land holdings and household size. Each farming household i is endowed with $\bar{n}_i^j$ units of time per farming stage and a plot of size l_i. Time endowments are allowed to vary proportionally to the time-length of the farming stage, i.e. land preparation typically accounts for 1/6th of the days of the agricultural season. Family workers elastically supply labor for farming activities or for activities outside the farm.

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. 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 hired workers need to be supervised to be productive.

a p-value of 0.4. These results are omitted for brevity but available upon request.

[24] This heterogeneous effect is present even when the elasticity of mechanization hours and employment are not statistically different across these populations.

5.1 Farming Households

A farming household i derives utility from consumption, c_i^j, and leisure, n_{il}^j in each stage $j = \{P, H\}$, with preferences that satisfy standard concavity and Inada conditions, $U(c_i^j, n_{il}^j)$. Family time $\bar{n}_i^j$ in each stage is assumed exogenous, and can be devoted to leisure, n_{il}^j, to working on the farm, n_{if}^j, to supervising workers on the farm, n_{is}^j, or to working outside the farm, n_{io}^j.

$$n_{il}^j + n_{if}^j + n_{is}^j + n_{io}^j = \bar{n}_i^j. \tag{2}$$

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.[25] Farming households consume over two periods and discount future consumption at the market interest rate, $R > 1$. For simplicity, we assume all non-farm labor engagement occurs when farm labor demand is low, i.e. at the land preparation stage.[26] We assume no working capital constraints, so factors are paid at the end of the season, once agricultural output has been realized.

$$c_i^P + \frac{1}{R}c_i^H = w_o n_{io} + \frac{1}{R}\pi_i. \tag{3}$$

Importantly, the supply of capital is exogenous to the farming sector, consistently with the low ownership rates for agricultural equipment observed in our data. Less than 2% of the sample own rotavators or cultivators, the main implements rented at this stage. Most rental services are provided by specialized firms, like our implementation partner, which are not directly engaged in farming.

5.2 Farming Technology

Let the size of a plot be l_i, capital services k_i, family labor n_{if}, and hired labor, n_i. 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. Gender differences are introduced again when parameterizing the model.

[25] Fewer than 2% of households report farming land that is not owned by the household, and we found no evidence of shifts in land allocation (likely due to the short-lived nature of the intervention).

[26] The model can be readily extended to allow engagement in both periods.

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_i^P, is a Cobb-Douglas function of land and tasks, m, that can either be performed by a machine, supervised labor, or family labor. These tasks include different extents of uprooting weeds during tilling, removal of stones, aerating, ripping, and leveling of the soil throughout the plot. Labor and capital are differentially suited for these tasks, which we capture through a profile of comparative advantage that tracks the marginal product of a unit of capital relative to labor in completing a task, $\frac{a_k(m)}{a_n(m)}$. For tractability, the model assumes a continuum of measure one of these tasks, so that output from the preparation stage is

$$y_i^P = \left(e^{\int_{m=0}^{1} \ln x_i(m)}\right)^{\alpha} l_i^{\alpha_l},$$

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

$$x_i(m) = a_k(m)k_i(m) + a_n(m)n_i^P(m,s) + a_n(m)n_{if}^P(m).$$

Family and hired labor at the preparation stage are n_{if}^P and n_i^P, respectively, and their marginal product in completing a task is assumed the same, $a_n(m)$. In addition,

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

That is, tasks are ordered so that capital is relatively more productive in those with lower index. Because labor and capital are perfect substitutes there is full specialization in tasks. Let M_i be the measure (or the share) of tasks that a farming household i decides to mechanize in a given plot.[27]

Harvesting stage. Output in the harvesting stage, y_i^H —i.e. final output — is a Cobb-Douglas aggregator of labor, land and output from the preparation stage.[28] To allow for shifts in labor needs due to mechanization of land prepa-

[27]In a slight abuse of interpretation, if mechanical tilling is only completed in half of a plot, we say that 50% of the tasks corresponding to that plot have been mechanized. The "comparative advantage" assumption is such that the subplot where ripping is mechanical is the one where the marginal product of capital is the highest.

[28]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 as shown in the

ration, we introduce a labor requirements shifter, $b(M_i)$, a technological feature that is common across farmers conditional on the mechanization threshold. Final output is then

$$y_i^H = y_i^P (\min\{n_{if}^H, b_f(M_i)\})^{\alpha_f^H} (\min\{n_i^H, b(M_i)\})^{\alpha^H} l_i^{\alpha_l^H}.$$

where the requirements function is assumed proportional for family and hired labor, i.e. $b_f(M_i) = \bar{b}b(M_i)$, for some constant $\bar{b}$, possibly below 1. 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 requirements may include, for example, 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. Family members can supervise workers, in which case they can catch a shirking worker with probability $\min\{\phi_i \frac{n_{is}^j}{n_i^j}, 1\}$. This probability increases with family labor engagement in worker supervision, n_s^j and depends on the farmer's supervision ability ϕ_i. For simplicity, we assume two levels of ability: low and high, $\phi_L < \phi_H$ and normalize high ability to $\phi_H = 1$. Because supervision labor is costly, farmers choose optimal supervision time to satisfy the incentive compatibility constraint of the worker, i.e. hired labor does not shirk if and only if the wage he gets is weakly higher than the expected return from shirking,

$$w \geq \omega w + \left(1 - \min\{\phi_i \frac{n_{is}^j}{n_i^j}, 1\}\right) w.$$

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

online appendix. Therefore, we abstract from this channel.

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 M_i such that all tasks with indexes $m < M_i$ will be mechanized, while all tasks with indexes $m > M_i$ will be completed with supervised labor or family labor (Acemoglu and Autor, 2011). A unique feature of our problem is that the shadow value of labor shifts whether farming households hire outside labor, which in turn has implications for the mechanization threshold through the marginal cost of labor relative to capital.

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 and factor allocations are the same across tasks produced by the same input. If M_i is the threshold for mechanization, the optimal allocation of hired labor is $n_i^P(m) = \frac{n_i^P}{1-M_i}$, that of family labor is $n_{if}^P(m) = \frac{n_{if}^P}{1-M_i}$, and the one of capital is $k(m) = \frac{k_i}{M_i}$.

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

$$y_i^P = A^P(M_i) k_i^{\alpha M_i} (n_i^P + n_{if}^P)^{\alpha(1-M_i)} l_i^{\alpha_l^P}.$$

where $A^P(M_i) = \bar{a}_k(M_i)\bar{a}_n(M_i)$ is an endogenous productivity term that depends on the mechanization threshold and the bias of technology (a_k, a_n).[29] 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. Given the above technology, we can solve for the optimal demand for family labor, supervised labor and capital as a function of the threshold M_i. Standard optimality conditions yield the key predictions for input allocation (as described in the Online Appendix).

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,

$$y_i^H = A^P(M_i) k_i^{\alpha M_i} (n^P + n_{if}^P)^{\alpha(1-M_i)} (n_i^H)^{\alpha^H} (n_{if}^H)^{\alpha_f^H} l_i^{\alpha_l}.$$

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

We assume constant returns to scale in inputs, i.e. $1 = \alpha + \alpha_l + \alpha_f^H + \alpha^H$, where $\alpha_l \equiv \alpha_l^P + \alpha_l^H$.

Worker supervision. The optimal supervision effort for the family is $s = \frac{\omega}{\phi}$,

$$n_{is}^j = \frac{\omega}{\phi_i} n_i^j. \tag{4}$$

Hence, supervision effort is proportional to hired labor in each stage, with a factor of proportionality that is independent of factor endowments and depends on the supervision ability of the farmer, i.e. higher ability requires lower supervision.

Household's labor supply decisions. How much hired labor and family labor gets allocated at each stage depends on the time available to the household and the return to working outside of agriculture.[30] If the wage outside agriculture is weakly higher than that in agriculture, $w_o \geq \frac{w}{1-\frac{\omega}{\phi_i}}$, the cost of hired labor is lower than the cost of 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. Labor demand is determined by land holdings and farm productivity, for fixed prices. 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 $w_o > \frac{w}{1-\frac{\omega}{\phi_i}}$.

6 Bringing the model to the data

In this section we describe the properties of allocation in terms of the relevant dimensions of heterogeneity. If the economy displayed aggregation, features of the average farmer would be enough to characterize outcomes in the economy, particularly welfare. Aggregation fails in our environment for two reasons: first, supervision needs imply that larger farming households find it relatively cheaper to supervise workers, all else equal; second, the shadow value of the household's time-endowment depends non-trivially on their decisions about farm produc-

[30] A full description of the equilibrium allocation is discussed in the online appendix. Here we summarize its main characteristics.

tion and labor supply through family-labor productivity in the farm, i.e. the non-separability hypothesis. Motivated by these margins, we characterize endowments and outcomes for the population of control farmers that hire workers and those that do not, as well as those that engage in non-agriculture and those that do not. Interestingly, the distribution of farmers along land, family size and capital-labor ratios in our set up is such that welfare gain in the economy with heterogeneity is very close to that of the average farmer.

Table 8: Heterogeneity along market participation margins

	share	$\ln(w_o n_o)$	$\frac{k}{l}$	$\frac{k}{n^P+n_f^P}$	$\frac{\pi}{n+n_f}$	l	$\bar{n}$ (count)	$\frac{n^P}{n^P+n_f^P}$	$\frac{n^H}{n^H+n_f^H}$
average	1	3.2	6.8	1.0	8.7	3.4	2.2	0.45	0.71
hire workers	0.53	.	7.3	0.6	8.7	3.3	2.2	0.62	0.77
	0.20	3.1	7.3	0.8	8.8	3.1	2.3	0.60	0.75
do not hire	0.15	.	6.4	2.2	8.6	3.4	2.3	.	0.61
	0.12	3.3	5.7	1.9	8.4	3.2	2.3	.	0.56

Summary stats for workers participating in the market for hired labor at land preparation (rows 2-5), and those participating in non-agricultural activities (rows 3 and 5). From left to right, we report the share of farmers that follow in each category, log non-agricultural income, mechanization hours per acre, capital-labor ratios at land-preparation, profits per worker, average plot size, household size and the ratio of hired worker-days to total labor input at lan-preparation and other stages.

The median farming household in our sample hires workers at land-preparation and does not engage in non-agricultural activities, while 15% of the farming households do not hire workers at land-preparation and do not engage in non-agricultural activities, see Table 8. These latter farmers are slightly less mechanized than those that hire labor at land-preparation (with average mechanization per acre of 6.4 hours vs. 7.3 hours), but are more mechanized than those that do not hire labor and instead take opportunities in non-agriculture (6.4 hours per acre vs. 5.7, respectively). There are no systematic differences in land or time endowments across those that hire labor at land preparation and those that do not, which would justify differences in the shadow value of family time and therefore observed capital-labor ratios at land-preparation (three times higher for those that do not hire workers).[31] We conclude that it is likely that the higher capital-labor ratios are associated with lower supervision ability, i.e. higher cost of hiring labor; and consistent with the lower ratio of hired to total labor input

[31] We report family size as members engaged in agriculture but the results follow the same patterns across these groups when counting all persons in the household.

observed at other stages of production.

One natural question related to disparities in observed capital-labor ratios is to what extent those reflect differences in mechanization thresholds rather than differences in capital demand for a fixed threshold. The next proposition explores these features.

Proposition 1. *Given the wage paid for farming workers, w, the wage earned in non-agricultural activities, w_o, supervision ability ϕ and the observed capital-labor ratios,*

1. *households that hire labor at land preparation have the same mechanization threshold irrespective of whether they engage in non-agricultural activities.*
2. *households that engage in non-agricultural activities have a mechanization threshold that is inversely related to their ability to supervise workers and this threshold coincides with (1) if observed capital-labor ratios coincide.*

   The mechanization threshold is independent of land and time endowments in (1) and (2).
3. *households that do **not** engage in non-agricultural activities and do **not** hire labor have mechanization thresholds that depend on time and land-endowments.*

6.1 Identification

Consistent with the experimental evidence, the parameter identification is focused on outcomes for the average farmer and we incorporate household heterogeneity when assessing channels and welfare.

6.1.1 Marginal Return to Capital

The production structure of the model yields

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

so that the returns to land are summarized by α_l while the returns to capital are summarized by α. M is the average mechanization threshold in the economy. There is an extensive literature in industrial organization and development economics describing the challenges of estimating these parameters. 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) 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 (Gandhi et al., 2020). The optimality condition with respect to capital yields an identification restriction for the share of capital in production, αM, which can be evaluated for the average farmer in our control group. The capital share for the control group satisfies,

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

and therefore identifies α conditional on the mechanization threshold, M.

6.1.2 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; as well as the structural relationship between the elasticity of output and total factor productivity to treatment. To make progress, we need an assumption on the shape of the bias of technology.

Assumption 2 Let the shape of the bias of technology satisfy $\frac{a_n(m)}{a_k(m)} \equiv \left(\frac{M}{(1-M)}\right)^{\beta-1}$ for $\beta > 1$.

Let $g\left(M\right) \equiv \frac{M}{1-M}\frac{a_n(M)}{a_k(M)}$ measure the equilibrium capital-labor ratio as a function of the mechanization threshold and the bias of technology.[32] The elasticity of the productivity residual A^P is a function of the shape parameter β and the elasticity of threshold to the subsidy,

$$A^P(M) = \left(\frac{\prod_{m=0}^{M}(1-m)^{\beta-1}}{M^M}\frac{\prod_{m=1-M}^{1} m^{\beta-1}}{(1-M)^{1-M}}\right)^{\alpha}. \tag{5}$$

[32]This is equivalent to assuming that the functional form for the bias of technology is an increasing function of M and a decreasing function of $(1-M)$, which satisfies Assumption 1. For example, $\beta = 2$ follows the specification of Acemoglu and Zilibotti (2001) for tasks performed by skilled and unskilled workers.

Hence, when combined with the response of output to treatment, it yields an identification restriction for the parameters of interest. The second identifying restriction for the parameters of interest corresponds to the equation linking the optimal threshold to observed capital-labor ratios.

$$\left(\frac{M}{1-M}\right)^{\beta} = \frac{k}{n_f + n^P}. \tag{6}$$

There are two challenges in computing the elasticity of the productivity residual to the change in the cost of capital, ϵ_{A_p}. First, such a residual is a function of the cost share of family labor which is unobserved; and second, it depends on the elasticity of family *productive* labor in the farm in both processes, also 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 6.2. Because capital and hired labor expenses are observable, the share of family labor can be estimated from farming 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 (74% of households report that the household head supervises).

6.1.3 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.

$$w_f = \alpha_f \frac{Y}{n_f^P + n_f^H + \omega n},$$

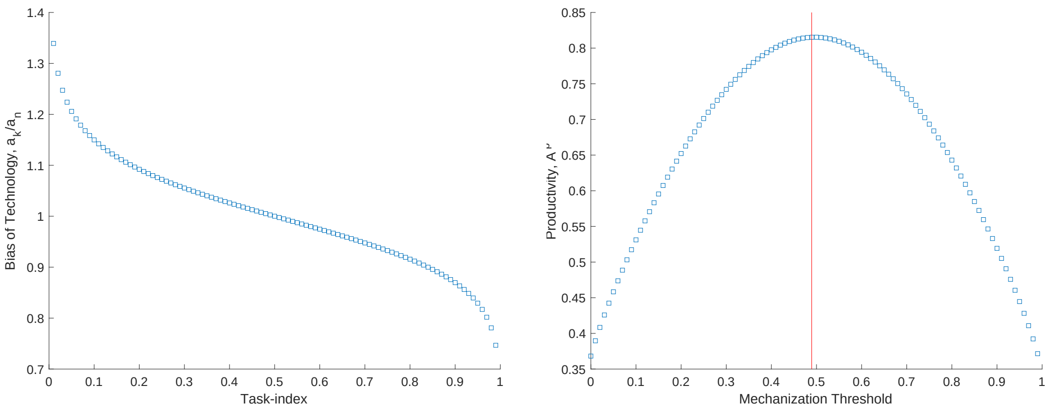
where $\alpha_f = 1 - \alpha^H - \alpha - \alpha_l$. That is, a fraction α_f of value added corresponds to the payments to family labor. All variables in this condition are observable, except for family supervision effort, ω. To discipline its value, we exploit the model's prediction for the optimal supervision time, i.e. proportional to hired labor, and the observed labor supply of family workers engaged in supervision at the preparation stage.[33]

[33] 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 favor our approach because it allows us to directly link changes in the friction to the elasticity of the

6.1.4 Changes in Contracting Frictions

To identify possible changes in 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, (see Table A7 for a value of the elasticity), $\epsilon_\omega = \epsilon_{\frac{n_s}{n}}$.

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.

6.2 Calibration

In this section we infer the threshold of mechanization for the average farmer in our sample, who hires labor at land-preparation. We parameterize factor shares and the profile of comparative advantage of capital vs. labor using the empirical results discussed in Section 4. Then, we test the model along untargeted moments, both for the average farmer and along the participation margins in the market for hired workers and non-agricultural activities.

Table 9 describes the parameterization of the model, where ϵ_x corresponds to the elasticity of variable "x" to treatment. 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 computation of returns to land can be found in Section 6.3. The elasticities of revenue per acre, capital per acre and family labor are as reported in Section 4. The moral

labor ratios from the experiment as in Section 6.1.4.

hazard parameter is inferred directly from the data using the model implications on the optimal family engagement in worker supervision in Section 5.4 and a normalization of supervision ability $\phi_H = 1$, i.e. the inverse of the measure of the span of control in Section A7. Supervision labor is allocated from working days of family members whose main activity is supervision and hired labor is computed for the whole agricultural season.

Table 9: Parameters fed directly from data

	Moment	Baseline		Source
A. Levels				
	$\frac{y}{l}$	₹26024		Control
	rk	₹2068		Control
	wn^P	₹2040		Control
	wn^H	₹15759		Control
	profits	₹6156		Table A8
	land holdings	3.3 acres		Control
	span of control	4.7 days		Table A7
B. Elasticities				
	$\epsilon_{\frac{y}{l}}$	0.0		Table A8
	$\epsilon_{\frac{k}{l}}$	0.101		Table A6
		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

Column (1) presents the benchmark parameterization while Column (2) presents the sources for the parameterization. Panel A. reports revenue, expenses and profits for the mean of the control group in our sample, as well as their ratio of mechanization hours to labor days at plant preparation and their ratio of supervision days to hired labor days over the season. Panel B. reports the relevant elasticities discussed in Section 4 (point estimates noisily estimated are assumed zero).

The shape of the bias of technology and the average mechanization threshold are jointly calibrated to match the implied elasticity of total factor productivity to the subsidy, see figure 1 as well the observed average capital-labor ratios. The labor requirements function at the harvesting stage is calibrated to match the decline in labor in downstream processes, while the factor of proportionality between family and hired labor requirements targets the share of family productivity labor to total labor at the harvesting stage (male equivalent days).

Heterogeneity in land and household sizes might be important when assessing welfare, even when the responses to the subsidy are similar along these dimensions. Given a measure of the incidence of the contracting friction ω, we calibrate the supervision ability of farmers that do not hire labor at land-preparation and receive non-agricultural income to match the ratio of hired labor to total labor days in stages other than land-preparation 0.56 (see Table 8), which yields $\phi_L = 0.34$.[34] This is the only parameter that is calibrated using information on heterogeneous land and family sizes and which help us rationalize the observed disparities in capital-labor ratios.

Table 10: Calibrated Parameters

	Parameter	Value	Target	Data	Model
Jointly					
	β	1.06	ϵ_{A^p}	0.05	0.04
	M	0.49	$\frac{k}{n^P+n_f^P}$	6.9	6.9
Separately					
	labor requirements				
	$b(M_{\text{treatment}}/b(M)$	0.86	ϵ_{n^H}	-0.056	-0.056
	$\bar{b}$	0.58	$\frac{n^H}{n^H+n_f^H}$	0.71	0.71
	heterogeneity				
	ϕ_L	0.34	$\frac{n^H}{n^H+n_f^H}\|_{n^P=0}$	0.56	0.56
	β_2		1.04	calibrated jointly	
	$\epsilon_{r,treatment}$		-0.09	experimental design	

Column (1) describes the parameter of interest, Column (2) its value, Column (3) the moment and Column (4) the value of the targeted. The elasticity of hired labor to treatment in stages other than preparation is computed for males, the base group (see Table 3).

6.2.1 Untargeted moments

We start by testing the performance of the model for outcomes of the average household in the sample, and then move to the distributional implications.

Participation in non-agriculture. The model calibration uses no information about non-agricultural activities because family engagement in the farm is derived from labor demand in farming given market prices. We use the predictions of the calibrated economy to test for the model goodness of fit in terms of non-agricultural engagement. If the average household engages in non-agricultural activities while hiring workers for farm production, the model

[34]We could have alternatively targeted the same moment for those that do not hire labor and do not engage in non-agriculture, results are available upon request. The disparities in the span of control are largest under the current calibration.

predicts an indifference condition between the cost of hiring labor at land preparation and the outside option for the farming household. The effective average cost of hired labor in the calibrated economy is $\frac{w}{(1-\omega)}$ =₹450, while the observed average daily wage in non-agriculture is ₹375. Hence, the model predicts non-engagement in agriculture, consistently with the median farmer in the sample; 68% of farmers do not work outside agriculture, see Table 8.

Change in the mechanization threshold The model was calibrated from observed levels and changes in capital-labor ratios for the average farmer. Through the lens of the model, a change in capital-labor ratios is consistent with changes in the cost of capital, or changes in the shadow price of family labor. The latter depends on profitability as well as on time endowments. The policy did not change endowments, and while the point estimate for profitability is positive, the effect is noisily estimated and set to zero in this quantitative exercise. We test whether the calibrated economy is consistent with the implied magnitude of the change in the cost of capital by totally differentiating the expressions for optimal capital-labor ratios and the mechanization threshold with respect to that cost.

The optimality condition for capital (in changes) and the marginal condition for the mechanization threshold characterizes the change in the threshold as a function of its level and the experimental elasticities as follows,

$$1 + \epsilon_{\frac{k}{l}} - \epsilon_{\frac{y}{l}} = \frac{1-M}{\beta}\epsilon_{k/(n_f^P+n^P)}. \tag{7}$$

In other words, the change in the expenditure share of capital should be commensurate with the change in capital-labor ratios at land preparation, an overidentification restriction for the model parameters. Albeit not targeted, we confirm the validity of this restriction at the calibrated parameters (the difference between the LHS and RHS is -0.05).

Heterogeneous participation in non-agriculture. The model calibration does not target the heterogeneous decisions of farmers to engage in work outside agriculture or whether to hire workers for land-preparation. We test the ability of the model to predict outcomes for these farmers, given their land and time endowments as well as supervision ability as described in Table 8. The model correctly predicts farmers engagement in the market for hired labor at land-preparation.

For farmers that do not hire workers, the model endogenously generates participation in non-agriculture activities given differences in time and land endowments, the calibrated parameters for the average farmer in the economy, and their supervision ability. For those that hire workers, differences in endowments are not enough to generate disparities in non-agricultural engagement. However, if we introduce the observed differences in profits per worker (1.1% higher than for those that do not engage in non-agriculture, see Table 8) the model endogenously generates positive engagement in non-agriculture.

Finally, the supervision ability of those that do not hire labor is calibrated using information from those that receive non-agricultural income. The model is however consistent with the share of hired labor in stages other than land-preparation for those farmers that do not hire labor at land-preparation and do not receive non-agricultural income, i.e. 0.56 versus 0.61 in the data.

6.3 Returns to Capital

To identify the marginal return to capital, 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 ₹240,000 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 land, and the assumption of constant returns. Table 11 presents these results.

At the mean, the expenditure share of capital expenses in value added is 8% while the expenditure share of labor at the preparation stage is 2% (consistent with a relatively low labor engagement). At the harvesting stage, the share of hired labor reaches 60%. The return to land is estimated at 2.2% and the remaining 27.2% is assigned to family labor. With this parameterization, we find that 47% of all mechanizable tasks are indeed performed by capital. This threshold implies a return to capital at the preparation stage of 17%, our main estimate.

Discussion. Our estimate of the return to capital could be sensitive to the computation of the returns to land, and through it, of the return to family labor, α_f. The reason is that the threshold is identified off of the elasticity of farm productivity to the subsidy which is a function of the elasticity of family labor

Table 11: Returns

αM	$\alpha(1-M)$	α_l	α_f^H	α^H	M	α
Baseline, frictionless capital markets						
8.0	9.0	3.7	18.9	60.5	0.47	16.9
Frictions, $MPK\tau = r$ for $\tau = 1.25$						
6.4	7.2	3.7	22.2	60.5	0.47	13.6

This table presents estimates of the inputs shares (in p.p.) for different factors of production, as well as the identified threshold for mechanization M 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.

to treatment (with a loading equal to its factor share, see equation 11). As an extreme, let us consider no return to family labor, i.e. all profits are accrued to land returns. The mechanization threshold decreases slightly to 46.9% (from 47% at benchmark) and the return to capital decreases slightly to $\alpha = 16.93\%$, from 16.94% in the baseline. We conclude that our estimate is robust to alternative measures of the returns to land.

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.[35] To explore the impact of these intrinsically unobserved frictions on equilibrium allocations, we model a gap between the marginal product of capital and the rental rate as $\tau \in (0, +\infty)$,

$$\frac{rk}{y^p} = \tau \alpha M \tag{8}$$

When $\tau \to 1$ the marginal product lines up with the market price, as $\tau \to 0$ the marginal product of capital goes to infinity and as $\tau \to +\infty$ the marginal product of capital declines to zero.

The mechanization threshold is identified from the elasticities of inputs and output induced by the experiment (given observed input expenditure shares), as well as the level of the capital-labor ratio to the control group and it is therefore

[35]In the experiment, samples are balanced in terms of our index of credit constraints and therefore, the estimates of the elasticities are robust to these constraints.

unaffected by the distortion. However, the mapping between capital expenses and the marginal return to capital is. We calibrate the wedge τ so that shadow value of family labor on the farm equals the market cost of labor, i.e. the average wage paid for hired labor by the control group (₹244). We obtain a wedge of $\tau = 1.25$, which yields a return to capital α of 13.6%. The reason is that family wages are computed as a residual from factor shares. Hence, for the family wage to raise relative to the benchmark, the share of capital needs to fall (increasing profits, ceteris paribus). It follows from equation 8 that τ should be larger than one. We use the former estimate as a lower bound to the estimated returns.

6.4 Family compensation and contracting frictions

As we mention in Section 6.1.3, it is possible to back-up family wages in the farm from the residual share of value added and family engagement in the farm in all activities. The implied wage per day for family workers in the farm is ₹207, slightly below the average wage for female workers and male workers in the farm (₹210 and ₹355, respectively), see Table A11. The difference between the cost of hired labor in the farm, ₹244 and the shadow value of family labor is 17% and the wedge to the outside option (wages in other farms ₹238) is 14.5%, consistent with contracting frictions that tie family workers to their farm, modeled in Section 5.3.

6.5 Experimental Findings Through the Lens of the Model

In what follows, we focus on the behavior of the average farmer and interpret the intervention with the shift in capital-labor ratios observed in the data. Let the value of the marginal product of labor at the preparation stage be $\tilde{w} \equiv w_{if}$ if $n^P = 0$ and $\tilde{w} \equiv w + \omega w_{if}$ if $n^P > 0$.

Fact 1 *The intervention induces mechanization.* Higher mechanization can be interpreted 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, optimality implies higher capital labor ratios in response to the subsidy to the cost of capital, for a fixed mechanization threshold M.

$$\frac{\tilde{w}}{r} = \frac{k}{n_f + n^P}\frac{1-M}{M} \tag{9}$$

The second channel is particular to a model of optimal task allocation: the marginal condition for mechanized tasks is

$$\frac{a_n(M)}{a_k(M)} = \frac{k}{n_f + n^P}\frac{1-M}{M} \tag{10}$$

Therefore, when capital is subsidized and capital labor ratios raise, the marginal mechanized task is higher, $M' > M$ under Assumption 1.

Fact 2 *Family labor falls at preparation* Lower family labor is a direct consequence of optimality, as follows from equation 9, 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.[36] 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, $\frac{\partial b(M)}{\partial M} < 0$, the demand for labor would decline even further.

Fact 3 *Labor hired at preparation does not change significantly* The point estimates are negative but noisily estimated.The model rationalizes the meager effects through small predicted changes in the mechanization threshold.

Fact 3.b *Labor hired falls at harvesting* Optimality requires that hired labor and family labor are proportional at the harvesting stage. 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

[36] For brevity, optimality conditions are described in detail in the Online Appendix.

[37] While we found no evidence of changes in market wages, the shadow value of family labor may have changed. The estimated shadow value of family labor for the calibrated economy, Section 6.2, is predicted to increase by 0.7p.p. .Absent changes in labor productivity at harvest-

effect of higher mechanization is negative, $\frac{\partial b(M)}{\partial M} < 0$, the demand for labor declines even further.

Fact 4 *Revenue per acre does not increase on average* Taking logs to the expression for output per acre and totally differentiating we obtain the effect of treatment on revenue as a function of the input elasticities to treatment

$$\epsilon_{\frac{y}{l}} = \underbrace{\epsilon_{A_p}}_{productivity} + \underbrace{(\alpha M)\epsilon_{\frac{k}{l}}}_{intensive-mech} \underbrace{-\alpha M \ln(\frac{k}{n_f^P + n^P})\epsilon_M +}_{extensive-mech}$$
$$\underbrace{\alpha(1-M)\epsilon_{n_f^P + n^P} + \alpha_f^H \epsilon_{n_f^H} + \alpha^H \epsilon_{n^H}.}_{labor-replacement} \tag{11}$$

Equation 11 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 corresponds to input intensification associated with the shift in capital-labor ratios. The third one is the *extensive-mechanization* term, which reflects another dimension of input intensification, through the change in the tasks performed by different factors. The fourth and last one is the *labor replacement effect*. The sign of the 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-agriculture 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 6.2.1, non-agriculture wages are indeed higher than the shadow value of wages on the farm, and therefore it is optimal for farming households to take opportunities in non-agriculture.

ing, 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.

Table 12: 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	6.2	5.5	5.5
B. Frictions in capital markets, $MPK\tau = r$ for $\tau = 1.15$.					
(1)	(2)	(3)	(4)	(5) -(2)+(3)+(4)	(6) (5)+(1)
0.0	0.7	0.0	6.5	5.8	5.8
C. Higher land share, $\alpha_l = 0.21$.					
(1)	(2)	(3)	(4)	(5) -(2)+(3)+(4)	(6) (5)+(1)
0.0	0.8	0.03	3.8	3.03	3.03

Each element of the table computes different channels through which a subsidy on mechanization affects revenue per acre, as characterized in equation 11. The elasticities to treatment and mean expenses for the control group are as described in Table 9 and input shares are reported in Table 11. 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 Quantifying Channels and Welfare

7.1 Effects on Productivity

In this section, we explore the channels affecting endogenous total factor productivity. In particular, we parameterize equation 11 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 and family labor per acre for the control, as reported in Table 3.

Table 12 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). In other words, the elasticity of the threshold to the change in the cost of capital is small. Finally, the labor replacement channel is positive at 6.2p.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 5.5.pp.

If instead we compute the total factor productivity for the economy with a wedge in capital rental markets, the implied productivity improvement is 5.8p.p. A higher productivity gain is explained by a stronger labor replacement channel (0.3p.p. higher due to a higher share of family labor in production), and a lower intensive mechanization channel, directly linked to the wedge in the rental capital market.

We also compute productivity changes assuming that the land share is higher than the currently estimated, and in line with previous estimates from cross-country evidence, i.e. 21% as estimated by Adamopoulos and Restuccia (2014). The estimated productivity gains are the smallest here, consistent with a weaker labor replacement effect in response to a lower share of family labor.

7.2 Welfare Effects From the Intervention

Table 13: Welfare

	Consumption-equivalent welfare	
	(a) γ_W	(b) γ_{W,n_l}
(1) Total	12.8%	5.2%
(2) Baseline	0.0%	0.0%
(3) More task-mechanized	-2.6%	9.6%
(4) (3) + Impact on inputs	4.9%	22.6%
(5) Labor requirements, harvesting.	2.7%	-0.5%
(6) Capital deepening	4.6%	1.6%
(7) Better supervision	12.8%	5.2%

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 from row 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 other stages to match the decline in labor from the experimental results. Row (6) includes the shift in capital per acre (extensive margin). Row (7) includes the shift in supervision requirements as estimated in Section 6.1.4.

We conclude the analysis of the implications of the experiment with a welfare calculation. Preferences are logarithmic and separable in consumption and leisure in each stage, $U(c_i^j, n_{il}^j) = \ln(c_i^j) + \ln(n_{il}^j)$. There are two periods that are relevant to the decisions of the household. Households discount future consumption at 2.46% over the five months that the agricultural season lasts, consistently with an annualized interest rate of 6%. Let consumption in the baseline economy be c_{ib} and let leisure in the land-preparation stage and non-land preparation stage be n_{ilb}^P and n_{ilb}^H, respectively.[38]

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

$$W(l_i, \bar{n}_i, \phi_i) \equiv \max_{c, n_l^j, n^j} U(c_i, n_{il}^P) + \frac{1}{R} U(c_i, n_{il}^H)$$

subject to the goods and time constraints as well as the incentive compatibility constraint for hired labor. 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.

$$(1 + \gamma_W) = \exp \frac{\int_i W(l_i, \bar{n}_i, \phi_i) d\mu}{\int_i W_b(l_i, \bar{n}_i, \phi_i) d\mu}$$

for μ the joint distribution of land and time endowments and supervision ability. 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, $\gamma_{W,nl}$.

$$(1 + \gamma_{W_{nl}}) = \exp \frac{\int_i W_{nl}(l_i, \bar{n}_i, \phi_i) d\mu}{\int_i W_{b,nl}(l_i, \bar{n}_i, \phi_i) d\mu}$$

where W_{nl} fixes the leisure allocation to its baseline level.

The consumption-equivalent welfare from the intervention is 5.2% over the season when we abstract from movements in labor supply, as shown in Table 14. If we include the change in leisure associated with the equilibrium response of labor to the subsidy, the consumption-equivalent welfare is substantially larger, 12.7%. In other words, the welfare gains from the intervention are split between higher leisure and higher consumption, on average. These effects are however heterogeneous across farmers as we show in Table 14. The welfare effect from changes in consumption is 3.8% for farmers with relatively high supervision ability and reaches 12% when considering the effects on leisure. The welfare effects

[38] Note that the optimal level of consumption is constant between land-preparation and non-land preparation for all households.

of the subsidy are always higher for farmers with low supervision ability, and the effect on leisure is heterogeneous whether these farmers engage in non-agriculture or not. Indeed, for those that engage in non-agriculture leisure falls. Quantitatively, these farmers account for 12% of the population and therefore leisure gains observed elsewhere drive the average effect.

The intervention induces welfare gains through a variety of channels which our structural model allows us to disentangle. This is particularly important given the sizable welfare gains that are accounted for changes in leisure. These are mostly explained by the improvement in supervision ability, which increases the span of control in the farm as observed in the experimental evidence. Absent this channel, the welfare gains from the intervention would be a third of the baseline, 4.6% instead of 12.8%.

In terms of welfare changes, not surprisingly, the largest contributors are the endogenous shift in the mechanization threshold and its impact on the demand for other factors of production, as well as the productivity improvement. The second most important contributor to welfare improvements is the reduction in supervision needs. The observed decline in labor demand in downstream stages has a sizable negative effect on welfare, mostly through its effect on consumption. In other words, farming households value the leisure gains from lower supervision at harvesting, but the observed decline in labor engagement has associated costs in farming output (consistent with the null evidence on revenues).[39]

Table 14: Welfare, heterogeneous effects

	hire		do not hire		Total
	(a)	(b)	(c)	(d)	(e)
γ_W	11.9%	11.8%	15.2%	9.3%	12.8%
γ_{W,n_l}	3.8%	3.8%	5.9%	11.6%	5.2%
share	0.53	0.20	0.15	0.12	
non-agriculture	no	yes	no	yes	

Welfare by farming types. Columns (a-b) correspond to farming households that hire workers at land-preparation and Columns (c-d) to farming households that do not.

[39] 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. When we account for the cost of the subsidy, the welfare gains are 0.7p.p. lower than the benchmark in Table 14.

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 3p.p. to 5.8 p.p. over the season. This improvement is reflected in 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. We identify a key margin through which the returns to mechanization are realized, output standardization. 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 15.5% and 17%, 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.[40]

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. 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 the intervention. 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.

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

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.

Acemoglu, D. and Guerrieri, V. (2008). Capital Deepening and Nonbalanced Economic Growth. *Journal of Political Economy*, 116(3):467–498.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Zilibotti, F. (2001). Productivity Differences. *The Quarterly Journal of Economics*, 116(2):563–606.

Adamopoulos, T. and Restuccia, D. (2014). The size distribution of farms and international productivity differences. *American Economic Review*, 104(6):1667–97.

Afridi, F., Bishnu, M., and Mahajan, K. (2020). Gendering technological change: Evidence from agricultural mechanization.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2020). What are the labor and product market effects of automation? new evidence from france. Technical report.

Akcigit, U., Alp, H., and Peters, M. (2020). Lack of selection and limits to delegation: Firm dynamics in developing countries. *American Economic Review*, Forthcoming.

Alvarez-Cuadrado, F., Van Long, N., and Poschke, M. (2017). Capital–labor substitution, structural change, and growth. *Theoretical Economics*, 12(3):1229–1266.

Bardhan, P. K. (1973). Size, productivity, and returns to scale: An analysis of farm-level data in indian agriculture. *Journal of political Economy*, 81(6):1370–1386.

Baumol, W. J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *The American Economic Review*, 57(3):415–426.

Bharadwaj, P. (2015). Fertility and rural labor market inefficiencies: Evidence from india. *Journal of development Economics*, 115:217–232.

Bloom, N., Garicano, L., Sadun, R., and Van Reenen, J. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science*, 60(12):2859–2885.

Bloom, N. and Van Reenen, J. (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives*, 24(1):203–24.

Brooks, W. and Donovan, K. (2020). Eliminating uncertainty in market access: The impact of new bridges in rural nicaragua. *Econometrica*, 88(5):1965–1997.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2020). The Macroeconomics of Microfinance. *The Review of Economic Studies*, 88(1):126–161.

Bustos, P., Garber, G., and Ponticelli, J. (2020). Capital Accumulation and Structural Transformation*. *The Quarterly Journal of Economics*, 135(2):1037–1094.

Caunedo, J., Kala, N., and Zhang, H. (2020). Economies of density and congestion in capital rental markets. Working paper.

Caunedo, J. and Keller, E. (2021). Capital obsolescence and agricultural productivity. *The Quarterly Journal of Economics*, 136(1):505–561.

Chakravorty, S. (2013). A new price regime: Land markets in urban and rural india. *Economic and Political Weekly*, 48(17):45–54.

Chandler, D. and Webb, M. (2019). How does automation destroy jobs? the 'mother machine' in british manufacturing, 2000-2015. Technical report.

Chen, C. (2020). Technology adoption, capital deepening, and international productivity differences. *Journal of Development Economics*, 143(C).

De Mel, S., McKenzie, D., and Woodruff, C. (2008). Returns to capital in microenterprises: evidence from a field experiment. *The quarterly journal of Economics*, 123(4):1329–1372.

Foster, A. D. and Rosenzweig, M. R. (1994). A test for moral hazard in the labor market: Contractual arrangements, effort, and health. *The Review of Economics and Statistics*, 76(2):213–227.

Foster, A. D. and Rosenzweig, M. R. (2017). Are there too many farms in the world? labor-market transaction costs, machine capacities and optimal farm size. Technical report, National Bureau of Economic Research.

Gandhi, A., Navarro, S., and Rivers, D. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8).

Gollin, D., Parente, S., and Rogerson, R. (2002). The Role of Agriculture in Development. *American Economic Review*, 92(2):160–164.

Graeub, B. E., Chappell, M. J., Wittman, H., Ledermann, S., Kerr, R. B., and Gemmill-Herren, B. (2016). The state of family farms in the world. *World Development*, 87:1–15.

Hayami, Y. and Ruttan, V. (1971). Agricultural development: An international perspective. *Johns Hopkins Press*, page 336.

Herrendorf, B., Rogerson, R., and Valentinyi, A. (2014). Growth and structural transformation. In *Handbook of Economic Growth*, volume 2, chapter 06, pages 855–941. Elsevier, 1 edition.

Humlum, A. (2019). Robot adoption and labor market dynamics. Technical report.

Janes, L., Koelle, M., and Quinn, S. (2019). Do capital grants improve microenterprise productivity? Technical report, Centre for the Study of African Economies, University of Oxford.

Jorgensen, M. H. (2018). The effect of tillage on the weed control: An adaptive approach. *Biological Approaches for Controlling Weeds; Radhakrisnan, R., Ed.; InTech: London, UK*, pages 17–25.

Kaboski, J. P. and Townsend, R. M. (2011). A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica*, 79(5):1357–1406.

Karlan, D., Osei, R., Osei-Akoto, I., and Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2):597–652.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and Firms*†‡. *The Economic Journal*. ueab009.

Kongsamut, P., Rebelo, S., and Xie, D. (2001). Beyond balanced growth. *The Review of Economic Studies*, 68(4):869–882.

LaFave, D. and Thomas, D. (2016). Farms, families, and markets: New evidence on completeness of markets in agricultural settings. *Econometrica*, 84(5):1917–1960.

Lagakos, D., Mobarak, A. M., and Waugh, M. E. (2018). The welfare effects of encouraging rural-urban migration. Working Paper 24193, National Bureau of Economic Research.

Monaco, T., Weller, S., and Ashton, F. (2002). Weed science, principles and practice. john wilay &sons inc. *New York*, pages 223–234.

Ngai, L. R. and Pissarides, C. A. (2007). Structural change in a multisector model of growth. *American Economic Review*, 97(1):429–443.

Rosenzweig, M. R. and Udry, C. (2014). Rainfall forecasts, weather, and wages over the agricultural production cycle. *American Economic Review*, 104(5):278–83.

Timmer, C. P. (1988). Chapter 8 the agricultural transformation. volume 1 of

Handbook of Development Economics, pages 275 – 331. Elsevier.

Udry, C. and Anagol, S. (2006). The return to capital in ghana. *The American Economic Review*, 96(2):388–393.

Proposition 1 (proof). The optimal allocation across tasks implies that the mechanization threshold satisfies,

$$\frac{\tilde{w}_i}{r} = \frac{a_n(M_i)}{a_k(M_i)} = \frac{k_i}{n_{if}^P + n_i^P}\frac{1 - M_i}{M_i} \tag{12}$$

where $\tilde{w}_i = w_{if} = w_o$ if the farmer works outside the farm, $\tilde{w}_i = w + \frac{\omega}{\phi_i} w_{if}$ if the farmer hires workers and $\tilde{w}_i = \frac{\mu_i}{\lambda_i}$ —the shadow value of time in units of the marginal utility of consumption, λ_i— if the farmer does not hire workers neither engages in work outside the farm.

1. It follows from the equality in capital-labor ratios between those that participate in non-agriculture versus those that do not and the fact that $w_{if} = \frac{w}{1-\frac{\omega}{\phi_H}}$ that the threshold of mechanization is identical across these households, see equation 12 and table 8.[41]

2. Consider farmers that engage in non-agriculture. For those that hire workers, $w_{if} = w_o = \frac{w}{1-\frac{\omega}{\phi_i}}$, while for those that do not, $w_{if} = w_o < \frac{w}{1-\frac{\omega}{\phi_i}}$. In the data, observed capital-labor ratios are higher for those that not hire outside labor, consistent with higher shadow cost, or lower supervision ability $\phi_L < 1$. Using equation 12 and the fact that $\frac{a_n(M_i)}{a_k(M_i)}$ is a strictly increasing function of the mechanization threshold (assumption 1) it follows that M_i is higher for those with lower supervision ability.

   The result on capital-labor ratios is identical to (1). In both (1) and (2), equation 12 implies that the mechanization threshold is independent of land and time endowments given market prices.

3. The mechanization threshold depends both on the land endowment and the time endowment, through their shadow value of time, i.e. $w_{if} = \frac{\mu_i}{\lambda_i} = \frac{c_i^P}{n_{il}^P}\bar{n}_i^P$.

   The marginal rate of substitution, i.e. the shadow price of family labor relative to consumption, can be computed nonlinearly from the feasibility

[41] When a farmer does not engage in non-agriculture, $\frac{w}{1-\frac{\omega}{\phi_H}} = w_{if} \geq w_o$ and when he engages in non-agriculture, $\frac{w}{1-\frac{\omega}{\phi_H}} = w_o$. Therefore, both conditions are satisfied if either the ability to supervise workers is lower for those that do not engage in non-agriculture than those that engage in it (and therefore their shadow value of outside labor is higher), or the shadow value of capital labor is indeed equal to w_o. Table 8 shows that capital-labor ratios are the same across farmers that hire workers irrespective of whether they engage in non-agriculture. Also, we find no difference in the span-of-control (measured as total supervision to working days) across these household and therefore no evidence suggesting differential ability across them, ϕ. In other words, in the plain-vanilla version of the model, those that hire outside labor and do not engage in non-agriculture and indifferent to this option.

conditions for goods and time and jointly with the mechanization threshold that follows from equation 12.

$$\frac{\mu_i}{\lambda_i} = \frac{\tilde{\gamma} y_i^H(\frac{\mu_i}{\lambda_i}, M_i)}{(1+1/R)} \frac{\bar{n}_i^P}{\bar{n}_i^P - \frac{(1-M_i)\alpha y^P(\frac{\mu_i}{\lambda_i}, M_i)}{\frac{\mu_i}{\lambda_i}}},$$

$$\frac{\frac{\mu_i}{\lambda_i}}{r} = \frac{a_n(M_i)}{a_k(M_i)},$$

where $\tilde{\gamma}$ is the share of agricultural output that accrues to the farming household (including land-returns, α_l). Hence, the shadow value of time relative to the shadow value of consumption is a function of the land and time endowment and so is the threshold.

□

A 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.[42]
- 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.[43]

[42] Average expenses by stage as reported in Table A10 are slightly higher than the implied ones following our methodology.

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

A Additional Tables

Table A1: 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 A2: 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 A3: 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 A4: Most Commonly Rented Implements

Commonly Rented Implements- Control Group			
	(1)	(2)	(3)
	N	Mean	Standard Deviation
1(Rented Cultivator)	2,969	0.62	0.12
1(Rented Rotavator)	2,969	0.36	0.48
1(Rented Mechanical Plough)	2,969	0.21	0.41

Commonly Rented Implements- Custom Hiring Centers	
	(1)
	Percent of Transactions
Cultivator	25%
Rotavator	22%
Disc Plough/Mechanical Plough	9.7%

Implements With Largest Available Inventory at Custom Hiring Centers
Cultivator 9 Tyne, Rotavator 6 Feet, Trolley 2-WD

Notes: All data for the kharif season of 2019. Panel 1 is from endline survey data.
Panels 2 and 3 are sourced from transaction-level data from the implementation partner.

Table A5: 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 A6: 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 A7: 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 A8: Output Per Acre: Treatment Effects

	(1)	(2)	(3)	(4)
	1(Output Sold)	Proportion Sold	IHS(Revenue/Acre)	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 A9: 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.
These results restrict the estimation to farmers who responded to survey questions on quantity sold, revenues, and profits.

Table A10: Labor and Capital Expenditure Per Acre

	(1) Mechanization	(2) Mechanization from Platform	(3) Non-Land Preparation Labor	(4) Land Preparation Labor
1(Mechanization)	-0.0410	2.058****	-0.119	-0.118
	(0.117)	(0.153)	(0.0774)	(0.106)
1(Cash and Mechanization)	0.155	-0.440****	0.0469	0.0249
	(0.126)	(0.124)	(0.0843)	(0.112)
Control Mean	2068.5	70.20	16935.5	2783.5
Observations	5444	5449	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).
Mechanization from Platform is the mechanization expenses in ₹per acre from the CHCs.
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 A11: 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.