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MECHANIZING AGRICULTURE

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ABSTRACT

What are the gains from mechanization? We run a randomized control trial that subsidizes access to equipment rental markets to study how the adoption of mechanization shifts farming households' labor supply, farm productivity and labor demand. The intervention induces greater mechanization in the upstream production stage, with labor savings concentrated in downstream, non-mechanized stages. Savings on family labor are concentrated among members engaged in worker supervision and accompanied by an increase in households' non-agricultural income. To assess the welfare implications of the intervention, we build a model of heterogeneous farmers that make joint labor supply and production decisions because incentives to mechanize depend on the opportunity cost of supervising hired labor. The calibrated model predicts a consumption-equivalent welfare improvement of 7.6%, with two-thirds of those gains accruing to leisure. Welfare gains are heterogeneous despite common treatment effects. Through counterfactuals, we show that endogenous productivity gains account for relatively more of the welfare gains for farmers with low-supervision ability.

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

1 Introduction

Economic activity in developing countries is labor intensive, low scale, mostly managed by family members (Akcigit et al., 2020) and concentrated in agriculture (Herrendorf et al., 2014).[1] A long tradition in development economics argues that an essential condition for economic growth is the adoption of technologies that increase agricultural productivity, releasing workers to other sectors of the economy.[2] In particular, mechanization is posited to be central to agricultural labor productivity, and is a primary feature of modern agriculture in developed countries.

In this paper, we employ a randomized control trial and a structural model to study how the adoption of mechanized practices affects aggregate labor demand, the demand for different types of labor (e.g. hired vs. family workers), and productivity in the farm, as well as labor supply decisions among families that run these farms. Capital intensification of labor intensive activities is transformative, but the channels through which it operates can be obscure, particularly in environments where frictions and unobserved characteristics affect adoption (De Janvry et al., 2017; Jones et al., 2020). We therefore favor an experimental approach combined with a structural model to help us elucidate both the nature of these channels and their magnitude.

Evidence on the path to mechanization for now rich economies suggests that equipment rental markets were a stepping stone to that process Binswanger (1986). Hence, the RCT is set up to estimate the impact of mechanization through rental markets, the most pervasive way in which smallholder farmers access mechanization. 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

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

[2] 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. Other contributions to these extensive literature include, Baumol (1967), Timmer (1988), Kongsamut et al. (2001), and Ngai and Pissarides (2007).

available equipment at custom hiring centers (CHCs) and valid for redemption throughout the season, allowing farmers to both optimally choose the technology and the use of equipment across agricultural stages of production. A subset of treatment farmers were given part of the value of the vouchers in the form of a cash transfer. Available equipment includes tractors and implements such as rotavators, cultivators and harrows.

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, especially in downstream, unmechanized stages. At the same time, labor savings are different for hired and family labor: while family labor is released throughout the season, displacement for hired labor is concentrated outside the land preparation stages and amongst female workers. Deep and multiple rounds of tillage during land preparation lowers the prevalence of weeds—contributing to the decline in female labor who largely specializes in weeding and harvest—, as well as ensures that planting happens in consistent rows, so that subsequent operations are easier to monitor (Monaco et al., 2002; Jorgensen, 2018).

Prior work has documented the existence of contracting frictions in agricultural labor, which induce specialization of tasks by family and hired labor (Bharadwaj, 2015; LaFave and Thomas, 2016). Accordingly, we investigate the mechanisms for the differential effects on labor types using detailed data on task specialization, at the household and individual level. First, as in earlier work, 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 from contracting frictions for hired labor, like moral hazard. Second, we find that the number of hired workers per supervising family member increases by 6.4 p.p. in

response to the subsidy, suggesting that family labor savings are stronger than those for hired labor. Finally, while we find positive effects on revenues, these are noisily estimated. 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 then build a structural model of farming with heterogeneous land holdings, time endowment and supervision ability to quantify the welfare effects of the intervention, as well as to study the relevance of different channels accounting for these effects. Farming is a multi-stage production technology where land preparation can be performed with machines or with labor (Acemoglu and Autor, 2011). Our main innovation relative to these prior models is that decisions to adopt mechanized practices depend on the shadow value of the households' 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. Farming households can be different in their supervision ability, and therefore in the cost of supervision per hired worker. In addition, the shadow value of the households' time can differ across households through their time endowment, i.e. the size of the family; and their labor supply choices, i.e. whether to engage in non-agriculture. A final innovation in the model is that, consistent with the empirical evidence, the measure of tasks performed in downstream activities (e.g. weeding) responds to the degree of mechanization at land-preparation.

We use the reduced form estimates from the experiment and the structural predictions to calibrate the model. Then, identification restrictions from the model allows to measure the marginal returns to capital and the shadow value of family labor on the farm, which are inherently unobservable.[3] We find that the marginal returns to capital are 15.9% per season under the assumption of frictionless rental markets, and can be closer to 18.6% when we allow for frictions in these markets. The model also shows that the shadow value of family labor is 10% below market prices, 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 farm, disparities in land holdings, time endowments, and supervision ability are enough for it to endogenously generate the observed heterogeneity in household participation in the market for hired labor at land-preparation.

Finally, we assess farmers' welfare from the intervention. Income changes are

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

not sufficient to assess welfare because the intervention shifts households' labor supply and the optimal leisure allocation across all stages of production. Furthermore, these shifts in labor supply and consumption are different for households that hold heterogeneous land and (family) time endowments. We construct a measure of consumption-equivalent welfare and find that the intervention raised welfare by 7.6%, with two-thirds of those gains accruing to leisure. We find evidence of heterogeneous welfare response among farmers with different time and land endowments, as well as supervision ability, despite a common treatment effect. Through counterfactual exercises, we show that the main contributor to the welfare gains among those with high-supervision ability is the direct effect of capital deepening on the marginal product of labor on the farm. Differently, the main contributor to the welfare gains among those with low-supervision ability is the endogenous response of total factor productivity, particularly through lower labor requirements in downstream stages. Disparities in supervision ability are inferred from disparities in hired to total labor input in the farm, given other characteristics. The magnitude of the endogenous productivity effect is inferred from the structure of the model and the empirical elasticities of output, labor and capital per acre. The productivity improvement that is consistent with the reduced for responses is 2.8% per season.

This paper is related to three main literatures. First, to our knowledge, this is the first causal evidence of the impact of mechanization, as well as of access to capital rental markets.[4] Mechanization in general and rental markets for mechanization in particular have been hypothesized as transformative for agricultural development Binswanger (1986), but causal evidence on how mechanization impacts productivity, labor demand, and labor allocation is lacking.[5] The role of capital intensification for agricultural productivity has been studied in Caunedo and Keller (2021) and Chen (2020). We provide the first available evidence of the micro-elasticity of productivity to mechanization, as well as its impact on labor demand on the farm and farmers' labor supply. We find that mechanization not only impacts labor demand via substitution, but also reduces labor demand in stages of production not being mechanized. Furthermore, the docu-

[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]In recent work, Afridi et al. (2020), uses soil characteristics to instrument for suitability for mechanization to estimate how mechanization affects labor use by gender.

mented reduction in the ratio of hired labor to supervision labor as a response to mechanization suggests that the adoption of mechanized practices may lower the incidence of frictions for hired labor, i.e. moral hazard.[6] We provide direct evidence on how capital intensification affects that link, and provide a framework where incentives to mechanize depend on the incidence of labor market frictions. Recent work Jones et al. (2020) show how such labor market failures impact the take-up of profitable technologies, namely irrigation. We show that while mechanization does not impact revenues, it does increase productivity via a variety of channels, which we quantify using the model.

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 not cost-effective.[7] 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 show how to overcome this obstacle by using identification restrictions from our structural model.[8] 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.

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

[6] More broadly, the link between moral hazard problems and the prevalence of small-scale producers has been studied in Bloom and Van Reenen (2010) and Akcigit et al. (2020).

[7] 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).

[8] 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).

quantitative measures remain elusive.

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 mean is 3.3 acres), and the most common crops are paddy (rice), cotton, and maize. Most 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 (we conducted a survey in 150 randomly selected villages to check how our sample compares to the average farmer in this setting, which we discuss later in the paper). 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

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

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 15.

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.

[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.

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 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 13, and is balanced

across treatment groups, though there is a small difference in the probability of being surveyed in person.[11]

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 16 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 14 presents summary statistics from the intervention sample, and the census data collection. The samples are largely comparable, though intervention households are slightly smaller than their population's counterpart.

3.4 Reduced Form Estimation

Our main estimating equation is as follows:

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

[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.

[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.

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 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 Table 20), 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

[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.

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

Table 1: Take-Up

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

Notes: Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
The dependent variable takes the value 1 if a farmer's phone number in the survey data could be matched to the mechanization rental platform data, and 0 otherwise.

Table 18 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 devi-

[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.

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.

ations 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 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.

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.

[16] While we report results for total mechanization hours, these should be interpreted as changes to land preparation mechanization. Table 19 presents treatment effects for land preparation only, and shows very similar treatment effects to considering overall mechanization.

Results are presented in Table 3. Family labor declines by similar magnitudes across gender, 16p.p. for males and by 16.6p.p. for females. These declines amount to 2.3 days of male family labor and 1.5 days of female family labor per acre. Hired labor displays heterogeneous effects by gender, with no significant shifts for males and a decline in female hired labor of 11.6p.p., significant at the 5% level. The decline in female hired labour amounts to 4.4 days of work per acre. This overall effect includes labor use across mechanized production stage (land preparation) and unmechanized production stages (all other downstream stages, namely, planting, plant protection, harvesting, and post-harvest processing). Next, we present results for labor demand separately by the mechanized stage (land preparation), and downstream, non-mechanized stages (combined labor demand for planting, plant protection, harvesting, and harvest processing). The second and third panel of Table 3 presents these results: we find that the treatment displaces primarily family labor for the mechanized stage, with little change for hired labor, either male or female. Mechanization reduces family male labor by 0.3 days per acre (10 p.p), and female family labor by about 0.07 days per acre (7.7 pp). For downstream stages, we find that while mechanization is labor substituting for all types of labor, the magnitude of the impact varies substantially by type of labor. For male labor, the effects are similar for family vs. hired male labor i.e. the treatment decreases demand for family male labor by about 1.7 days per acre (13 p.p.), and for hired male labor by about 1.3 days per acre (5.7 p.p.). In contrast, the effects are quite different for female labor– mechanization reduces demand for family female labor by about 1.1 day per acre (13.9 p.p), and by female hired labor by over 3 times more, about 4.2 days per acre.[17]

4.3 Task Specialization

Mechanization is labor-substituting, with the elasticity of substitution varying across types of labor e.g. family and hired labor. In this section, we explore whether differential task engagement by labor types may be source for this heterogeneity. We construct two measures of labor engagement. The first one

[17]In Table 21, 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 (Table 22). 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

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

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

collects information on all tasks ever performed by different types of labor while the second one only uses information on the tasks-listed-first for each type of labor.[18] Table 4 shows that tasks performed by different types of labor vary substantially.[19]

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 counter-

[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.

[19]Table 24 shows results with the tasks-listed-first instead of tasks-ever-listed but the allocation of tasks across labor groups are strikingly similar across measures.

parts and to hired labor. Several other tasks are gendered rather than segregated across family versus non-family labor – for instance, weeding and transplanting are primarily performed by women, whereas land preparation and manure application are primarily done by men. This task specialization and the differential impact observed on hired workers in other stages of production is suggestive of the impact of mechanization of land preparation on other tasks within the farm.

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 lowers the prevalence of weeds and therefore the need to employ labor to remove those weeds. It also ensures that planting happens in consistent rows, which could facilitate monitoring of subsequent operations (like harvesting).

To explore the link between task specialization and the nature of labor savings, we bring in task-engagement data at the individual-level.[20] We test whether family members whose primary task is supervision are differentially supplying lower labor on the farm in response to mechanization. To do so, we ask about tasks performed by each household member as well as days of labor on the farm, for up to four members most engaged in agriculture. 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. Column 1 in Table 5 shows that the probability that a household member reports supervision as their primary task does not change as a result of treatment. Column 2 shows that household members that report supervision as their primary task respond with 3.06 percent lower days per acre relative to members whose primary specialization is in other tasks.

Family labor engagement in supervision activities is consistent with moral hazard problems in farming activities. 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).

Supervision Labor Relative to Hired Workers. Given that farms are overwhelmingly managed by male family labor, we now test how the labor effects of the intervention impact the ratio of hired workers to supervising workers (i.e. the span of control) on the farm. To measure this ratio, use season-level hired

[20]Elsewhere, we report results at the household-level rather than at the individual level.

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.

labor use and individual task specialization data to construct two measures of the span of control. The first is the number of hired workers per household member who reported supervision as one of the tasks they performed on the farm.[21] The second is more directly linked to our measures of labor demand, i.e. the total number of days per acre of hired labor, divided by the number of days worked on the farm by households members that reported supervision as one of their tasks.

Table 6 show that the ratio of hired workers to supervising labor increases in response to treatment by 6.5p.p., i.e. there are additional 1.6 hired workers per family male supervising worker. Table 23 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.

Note that if family labor is held fixed, and family and hired labor are perfect substitutes, any labor-saving technology would reduce the ratio of hired labor to family labor, i.e. a decline in the span of control.

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

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

Table 5: Family Members' Supervision Engagement: Treatment Effects

	(1) 1(Supervision Primary Task)	(2) IHS(Days per Acre)
1(Mechanization)	-0.0128	-0.0579***
	(0.00951)	(0.0181)
1(Cash and Mechanization)	0.0187	0.00627
	(0.0128)	(0.0194)
1(Mechanization) X 1(Supervision Primary Task)		-0.0306**
		(0.0136)
1(Cash and Mechanization) X 1(Supervision Primary Task)		0.0153
		(0.0202)
1(Supervision Primary Task)		-0.00688
		(0.00778)
Control Mean Levels	0.480	0.570
Observations	15926	15801

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

Table 6: Hired 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.

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 28). We estimate a return on the subsidy of 64% for the average farm 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.

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.

4.4 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.

4.5 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. Hence, 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. The intervention does not seem to have induced new technology adoption – we observe no shifts in crop choices and 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).[22] We therefore favor the interpretation of a shift in the relative cost of capital to labor.

5 A Model of Mechanization and Farmers' Labor Supply.

Next, we present a model to interpret the effects of the experiment and its welfare implications. The model highlights that welfare gains from mechanization depend on farmers' engagement on the farm and in non-agriculture, as well as on the intensity of use of hired labor relative to capital at baseline.

The economy consists of a continuum of heterogeneous farming households that differ in land holdings and household size. Farming entails two stages: land preparation, *preparation* henceforth; and planting, plant protection, harvesting and processing, *harvesting* henceforth. Each household i is endowed with $\bar{n}_i^j$ units of time per farming stage and a plot of size l_i. Family workers elastically supply labor for farming or for non-agricultural activities.

Output from the preparation stage is used as an input for the harvesting stage.[23] Farmers use land, capital and labor to produce, and take input prices as given. Our empirical findings suggest that the intervention affected mechanization only at the preparation stage, so we assume that harvesting is only performed with labor. Finally, due to moral hazard in hired labor, family time is partially allocated to worker supervision. A farming household can simultaneously devote time to worker supervision and to productive labor on the farm.

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

[23]We abstract from uncertainty in returns to agricultural activities typically linked with weather shocks, (Rosenzweig and Udry, 2014), because mechanization had no direct impact on channels that could have affected the ability of farmers to shifts returns in response to these shocks. For example, it did not induce crop switching towards more resistant varieties (see Table 25).

We abstract from worker gender to ease the exposition, but introduce it again when parameterizing the model.

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 $U(c_i^j, n_{il}^j)$ that satisfy standard concavity and Inada conditions. Preferences are separable in consumption and leisure. Family time $\bar{n}_i^j$ 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, and 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 as well as any unpaid family labor.[24] 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.[25] We assume no working capital constraints, so factors are paid at the end of the season, once agricultural output has been realized.

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

The supply of capital is exogenous to the farming sector, consistently with the low ownership rates for agricultural equipment (less than 2% of farmers owns a rotavators or a cultivator) and the fact that most rentals are provided by specialized firms.

5.2 Farming Technology

Preparation stage. Output from the preparation stage, y_i^P, is a Cobb-Douglas aggregator of land and a continuum of tasks, m, that can either be performed by a machine, hired labor, or family labor,

[24] Fewer than 2% of households report renting land for farming, and we have no evidence of shifts in land ownership.

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

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

Tasks include uprooting weeds during tilling, removal of stones, aerating, ripping, and leveling off the soil throughout the plot. Output from each task is $x_i^P(m) = a_k(m)k_i(m) + a_n(m)n_i^P(m,s) + a_n(m)n_{if}^P(m)$, capturing the different suitability of labor and capital in completing them. This suitability is summarized through a profile of comparative advantage that tracks the marginal product of a unit of capital relative to labor in completing a task, $\frac{a_k(m)}{a_n(m)}$. Family and hired labor at the preparation stage —n_{if}^P and n_i^P, respectively— have the same marginal product, $a_n(m)$.

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

Hence, capital is relatively more productive in tasks labelled with a lower index. Because labor and capital are perfect substitutes in each task, there is full specialization in tasks. Let M_i be the measure (or the share) of tasks that are mechanized in the family plot.[26]

Harvesting stage. Output in the harvesting stage, y_i^H —i.e. final output — is a Cobb-Douglas aggregator of land, output from the preparation stage and a measure of tasks performed by labor. The measure of these tasks depends on the degree of mechanization at land-preparation, i.e. labor requirements $(b_f(M_i), b(M_i)) > 0$ for family and hired labor, respectively. These requirements may differ between family and hired labor because workers specialize in different tasks. For example, marketing activities are exclusively done by family labor, so improvements in productivity from mechanization might increase requirements for family labor; weeding is mostly done by hired labor, so lower weeding needs from mechanization of land-preparation might induce lower requirements for hired labor. Output from each task is a linear function of labor, $x_{if}^H(m) = n_{if}^H(m)$ and $x_i^H(m) = n_i^H(m)$. Output at harvesting is,

$$y_i^H = y_i^P \left(e^{\int_{m=0}^{b_f(M)} \ln(x_{if}^H(m))}\right)^{\alpha_f^H} \left(e^{\int_{m=0}^{b(M)} \ln(x_i^H(m))}\right)^{\alpha^H} l_i^{\alpha_l^H}.$$

[26] 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.

5.3 Contracting Problem

Workers' effort in the field is not observable. If a worker shirks, no hours are allocated to production and she gets a benefit proportional to the market wage, ωw. Therefore, ω is a measure of the incidence of the friction induced by the unobservability of effort. Family members can supervise workers, catching a shirking worker with probability $\min\{\phi_i \frac{n_{is}^j}{n_i^j}, 1\}$. This probability increases with family engagement in worker supervision, n_s^j and their supervision ability ϕ_i. Because supervising labor is costly, farmers choose optimal supervision time to satisfy the incentive compatibility constraint of the worker, i.e. a worker does not shirk if and only if the wage she gets is weakly higher than the expected return from shirking,

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

5.4 Optimal Allocations

Preparation stage. The optimal allocation of inputs to tasks given prices is such that the value of the marginal product for hired workers is the same irrespective of the task they perform. The optimal allocation of family labor and capital across tasks also shares this feature.

Given Assumption 1, it is straightforward to show that there exist a threshold M_i such that all tasks with indexes $m < M_i$ are mechanized, while all tasks with indexes $m > M_i$ are completed with hired labor or family labor (Acemoglu and Autor, 2011). A unique feature of our problem is that incentives to mechanize depend on moral hazard in labor and farming households' value of time, i.e. the cost of hiring labor depends on the shadow value of family time, through supervision needs.

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 tasks, and that factor allocations are the same for tasks produced by the same input. The optimal allocation of hired labor is $n_i^P(m) = \frac{n_i^P}{1-M_i}$, the one of family labor is $n_{if}^P(m) = \frac{n_{if}^P}{1-M_i}$, and the one of capital is $k(m) = \frac{k_i}{M_i}$, so we can rewrite output land-preparation 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).[27]

The optimal level of mechanization is a function of the bias of technology and the relative cost of capital and labor:

$$\frac{\tilde{w}_i}{r} = \frac{a_n(M_i)}{a_k(M_i)} = \frac{k_i}{n_{if}^P + n_i^P}\frac{1-M_i}{M_i}, \tag{4}$$

where $\tilde{w}_i = w_{if} = w_o$ if the farmer works outside the farm and does not hire workers; $\tilde{w}_i = w + \frac{\omega}{\phi_i}w_{if}$ if the farmer hires workers; and $\tilde{w}_i = \frac{U_{li}}{U_{ci}}$ if the farmer does not hire workers and does not engage in work outside the farm.

Harvesting stage and final output. A consequence of optimality is that the amount of labor allocated across tasks at harvesting is the same, i.e. $n_i^H(m) = n_i^H$and $n_{if}^H(m) = n_{if}^H$. Final output reads

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

where $\alpha_l \equiv \alpha_l^P + \alpha_l^H$, and the endogenous productivity term combines productivity from the land-preparation stage and labor productivity from the harvesting stage, $A(M_i) = A^P(M_i)b(M_i)^{-b(M_i)\alpha^H}b_f(M_i)^{-b_f(M_i)\alpha_f^H}$.

Worker supervision. The optimal supervision effort for the family is

$$n_{is}^j = \frac{\omega}{\phi_i}n_i^j. \tag{5}$$

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 time per hired labor.

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 in non-agriculture.[28] If the wage in non-agriculture is weakly higher than the cost of hiring a worker in agriculture, $w_o \geq \frac{w}{1-\frac{\omega}{\phi_i}}$, family labor would be mostly devoted to non-agriculture and only some family labor will engage in worker supervision. If the opposite holds, then family labor

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

[28] A full description of the equilibrium allocation is discussed in the Appendix D.1. Here we summarize its main characteristics.

will be engaged in productive activities in the farm. Labor will be hired if the farming labor demand is high relative to the size of the farming household. Labor demand is determined by land holdings and farm productivity, given prices. If family labor does not engage in either supervision or productive farming labor, the farm can only operate 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 wage premia in non-agriculture is positive $w_o > \frac{w}{1-\frac{\omega}{\phi_i}}$.

Hired labor allocation across stages. It follows from optimality that if the farming household hires labor in both stages, the amount of labor at harvest is proportional to that at the land-preparation stage, i.e. $n_i^H = \frac{\alpha^H b(M_i)}{\alpha(1-M_i)} n_i^P$. Hence, the direct effect of a higher share of mechanized tasks is an increase in the demand for labor at harvesting. This force is counteracted by a substitution effect that lowers the demand for labor at land preparation, n_i^P, and a labor requirements effect at the harvesting stage, through a decline in the measure of tasks that need to be completed for production, $\frac{\partial b(M_i)}{\partial M_i} < 0$.

Appendix C explains how the mechanisms embedded in the model rationalize the main empirical findings of the intervention.

6 Bringing the model to the data

In this section we use the model to disentangle the relevance of different channels through which the intervention shifted allocations, and its welfare implications. We solve for optimal labor supply decisions of the farming households and optimal labor demand decisions in the farm in both stages of production, taking as given wages and the increase in mechanization hours induced by the experiment. We found no evidence of general equilibrium effects through the cost of labor so we assess welfare accordingly.[29] We also found no evidence of heterogeneous effects on take up or mechanization hours across farmers of different characteristics, so we simulate a common increase in mechanization hours.

Before discussing the model parameterization, it is important to describe the relevant dimensions of heterogeneity across farmers. If the economy displayed aggregation, features of the average farm would be enough to characterize outcomes

[29] General equilibrium effects on the labor market might be particularly important from subsidy schemes at scale, and a relevant dimension of study for future research on the incidence of mechanization.

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 production and labor engagement in non-agriculture, i.e. the non-separability hypothesis. Motivated by these margins, we characterize endowments and outcomes for the population of control farmers that hire workers at land preparation and those that do not, and for those that engage in non-agriculture and those that do not.

Table 8: Heterogeneity along market participation margins

sample	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)	$\frac{n^P}{n^P(1+s)+n_f^P}$	$\frac{n^H}{n^H(1+s)+n_f^H}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
average	1	3.2	6.8	1.0	8.7	3.3	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 statistics for workers that hire labor at land preparation (rows 2 and 3), and those participating in non-agriculture (rows 3 and 5) for the control group. From left to right, we report the share of farmers 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 land-preparation and harvesting.

The median farming household in our sample does not engage in non-agriculture and hires workers at land-preparation, see Table 8. Farmers in autarky —those that do not engage in non-agriculture and do not hire workers— account for 15% of the farming households and 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). Those that do no hire labor at land-preparation but engage in non-agriculture are the least mechanized, with 5.7 hours per acre. 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).[30] We

[30] We report family size as members engaged in agriculture but results are robust to counting all persons in the household.

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 labor to total labor input observed at stages of production other than land-preparation. So, given supervision ability, do differences in capital-labor ratios reflect disparities in mechanization thresholds, or disparities 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-agriculture, 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-agriculture.*

2. *households that engage in non-agriculture 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-agriculture and do not hire labor have mechanization thresholds that depend on their time and land-endowments.*

The reason for which time and land endowments are not relevant for observed mechanization whenever farmers participate in non-agriculture, is that the cost of family labor is pinned down by market prices. If the farmer does not participate in non-agriculture but displays capital labor ratios comparable to those farmers that do participate, then mechanization choices are observationally equivalent to those pin down by market prices (given supervision ability).

6.1 Calibration

We calibrate a total of 33 parameters: 16 parameters are disciplined from characteristics of the average farm in the control group and the experimental elasticities; 10 parameters characterize farm heterogeneity; and the remaining 7 parameters are calibrated jointly by solving the model. Then, we test the model along untargeted moments.

First, parameters calibrated outside the model for the average farm include the time endowment in each stage, cultivated land, the expenditure shares in

capital and labor in each stage, the return to family labor in each production stage, and the return to land (see Panel A of Table 9). The time endowment is a function of the number of household members and scales proportionally to the time-length of the farming stage, i.e. land-reparation accounts for 15 days, or 1/6th of the agricultural season. The land endowment corresponds to the size of the plot cultivated by the household.The capital expenditure share is 8% while the expenditure share of labor at the preparation stage is 4.0% ($\frac{n^p}{n^P+n_f^P} * 8.0\%$). At the harvesting stage, the expenditure share for hired labor is 60.5%, see Table 30. These shares are computed as a ratio of expenses in each input divided by farm revenues. Farm revenues are net of intermediate input expenses because we model value-added. The computation of the return to land exploits the Euler equation for a durable good, $r_{t+1} = p_t(R_y - (1-\delta)\frac{p_{t+1}}{p_t})$. We assume a real interest rate of $R_y = 1.06$ per year; a physical depreciation rate for land of $\delta = 2\%$ per year; and set the price of land at $p_t = ₹240,000$ per acre, consistent with the estimates in Chakravorty (2013). The expectation for appreciation in the price of land is set at $\frac{p_{t+1}}{p_t} = 8\%$ per year, yielding a user cost of ₹574 per acre per year, or a cost share of land $\alpha_l = 4.9\%$.[31]

To solve for labor allocations we need a measure of the incidence of moral hazard, and the wage in agriculture relative to non-agriculture (see Panel B of Table 9). Inference of the incidence of moral hazard parameter ω relies on the model implications for optimal family engagement in worker supervision in Section 5.4, $\omega = \frac{n^H}{n^H_{fs}}$, normalizing the supervision ability of the average farmer to 1. Supervision labor is allocated from days worked by family members whose main activity is supervision, and hired labor is computed as full-time equivalent males for the whole agricultural season. Because the model displays no gender, we measure employment as the full-time-equivalent males working on the farm, using average wages between males and females to adjust working days for females on the farm. The relative wages in agriculture and non-agriculture are measured as averages for the control group, while the level of the real wage is normalized to 1. Finally, we use the the elasticity of revenue, mechanization hours, and labor per acre (see Panel C of Table 9) to discipline responses to treatment. The elasticity of full-time-equivalent males to the subsidy is an employment weighted average of the elasticity of females and males.

[31] We discuss sensitivity analysis with respect to this estimate in Section 7.1.

Table 9: Parameters calibrated outside the model

Description	Parameter	Value	Source
A. Average farm			
A.i. production technology			
labor share harvesting	α^H	₹$\frac{15759}{26024}$=60%	Control
land share	α^l	4.9%	Euler Eq.
land holdings	l	3.3	Table 8 c.6 r.1
labor requirement, harvest	$b(M)$	1.0	Normalization
A.ii. labor choices			
hired to supervision labor	ω	1/4.7 days	Table 23
supervision ability	ϕ_h	1.0	Normalization
relative wage non-agriculture	$\frac{w_o}{w}$	1.05	Control
discount factor	R	2.4%	$R_y = 6\%$ (annual)
time-endowment, land-prep	$\bar{n}^P$	2.2 x 15 days	Table 8 c.7 r.1
time-endowment, harvesting	$\bar{n}^H$	$\bar{n}^P$ x 9	Season length
real wage agriculture	w	1.0	Normalization
A.iii. residual productivity shifter			
output per acre	$\epsilon_{\frac{y}{l}}$	0.0	Table 26 c.3
capital per acre	$\epsilon_{\frac{k}{l}}$	0.1	Table 19 c.1
family labor land-prep	$\epsilon_{\frac{n_f^P}{l}}$	-0.1	Table 3 c.1, c.3
hired labor land-prep	$\epsilon_{\frac{n^P}{l}}$	0.0	Table 3 c.2, c.4
family labor harvesting	$\epsilon_{\frac{n_f^H}{l}}$	-0.1	Table 3 c.1,c.3
B. Farm Heterogeneity			
land holdings	l_i	3.1-3.4	Table 8 c.6 r.3-6
capital-labor ratios	$\frac{k_i}{n_i^P+n_{fi}^P}$	1.1-2.2	Table 8 c.4 r.1, r5-6
time-endowment, land-prep	$\bar{n}^P$	2.2-2.3 x 15 days	Table 8 c.7 r.3-6

Panel A. reports parameters calibrated parameters for the average farm while Panel B. reports the relevant parameters that differ across farms. The experimental elasticities discussed in Section 4 and used for calibration are set to zero whenever point estimates are noisily estimated.

Second, parameters calibrated outside the model that characterize farm heterogeneity include cultivated land, family time endowments, capital-labor ratios at baseline, which are calibrated using information in Table 8.

Third, parameters calibrated jointly include the shape of the bias of technology, the average mechanization threshold, family labor requirements relative to hired labor requirements at the harvesting stage at baseline, the change in labor requirements for hired labor in response to treatment, the return to capital, the return to family labor at harvesting and the supervision ability of those that do not hire labor at land-preparation (see Table 10).

These parameters jointly match the implied elasticity of total factor productivity to the subsidy, the average capital-labor ratios, the expenditure share of capital, the share of family labor in total labor at the harvesting stage, the elasticity of employment at the harvesting stage to the subsidy for the average farm,

the ratio of hired labor to total labor input at harvest for farmers that do not hire labor at land-preparation and receive non-agricultural income. We exploit the assumption of constant returns to residually infer the returns to family labor at the harvesting stage for a measure of the returns to capital.

We normalize the labor requirements of hired labor at baseline to $b(M) = 1$, which yields baseline family labor requirements of $b_f(M) = 0.65$, a parameter closely related to the share of family labor in total labor at the harvesting stage for the average farm. We identify supervision ability using the share of family labor in total labor at the harvesting stage for farmers that do not hire at land preparation and participate in non-agriculture, $\phi_L = 0.34$, $\phi_L < \bar{\phi} = 1$ where $\bar{\phi}$ the ability of the average farmer.[32] This parameter is identified for a measure of the incidence of the contracting friction ω and a measure of family labor requirements, $b_f(M)$. Identification of the shape of the bias of technology requires an additional assumption,

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 $\beta > 1$.[33]

The equilibrium relationship between capital-labor ratios, the mechanization threshold and the shape parameter β provides a first identification restriction:

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

The elasticity of total factor productivity to treatment is also a function of the shape parameter and the mechanization threshold, as well as the change in labor requirements, which provides a second identification restriction:

$$A(M) = \left(\frac{\prod_{m=0}^{M}(1-m)^{\beta-1}}{M^M}\frac{\prod_{m=1-M}^{1} m^{\beta-1}}{(1-M)^{1-M}}\right)^{\alpha}\left(\frac{1}{b(M)^{b(M)}}\right)^{\alpha^H}\left(\frac{1}{b_f(M)^{b_f(M)}}\right)^{\alpha_f^H}. \tag{7}$$

These two identification restrictions plus empirical measures of the change in total factor productivity and the change in hired labor at harvesting identify the parameters of interest. The estimated shape parameter is $\beta = 1.23$ and the mechanization threshold at baseline is $M = 0.5$. The measure of tasks for

[32] 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 ratio between supervision labor and hired workers are largest under the current calibration.

[33] This shape embeds a variety of biases including Acemoglu and Zilibotti (2001), who pick $\beta = 2$ for tasks performed by skilled and unskilled workers.

Table 10: Jointly Calibrated Parameters

Parameter	Value	Relevant Moment	Data	Model
A. Average farm				
β	1.23	ϵ_A	2.8%	3.2%
M	0.5	$\frac{k}{n^P+n_f^P}$	1.1	1.0
$b(M_{\text{treatment}})/b(M)$	0.98	ϵ_{n^H}	-0.06	-0.06
$b_f(M)$	0.65	$\frac{n^H}{n^H+n_f^H}$	0.71	0.71
α	15.9%	$\frac{rk}{y}$	7.9%	7.9%
α_f^H	18.6%	$1-\alpha-\alpha_l-\alpha^H$	18.6%	18.6%
B. Farm heterogeneity				
ϕ_L	0.34	$\frac{n^H}{n^H(1+s)+n_f^H}\vert_{n^P=0}$	0.56	0.56
Mean squared error		0.0011		

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 at harvesting is computed as an employment weighted average of the elasticities of males and females (Table 3) with a weight of 0.51 for males.

hired labor after treatment declines by 1.2% to $b(M_{\text{treatment}}) = 0.989$, where $M_{\text{treatment}}$ is the new mechanization threshold. The mean squared error for this parameterization is 0.001.

6.1.1 Untargeted Moments

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

Mechanization and the implied change in the cost of capital. The model was calibrated from observed levels in capital-labor ratios for the average farm. 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,

$$1 + \epsilon_{\frac{k}{l}} - \epsilon_{\frac{y}{l}} = \epsilon_M = \frac{1-M}{\beta}\epsilon_{k/(n_f^P+n^P)}. \tag{8}$$

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 -0.04).

Decline in family labor requirements. The model is consistent with the decline in family labor at harvesting observed in the data (although the measure of tasks performed by family labor is held constant).[34] Such a decline is induced by the optimal relationship between hired and family labor for production and supervision, and the lower requirements for hired labor in response to treatment. Quantitatively, the model generates an elasticity of family labor to treatment of -8.5%, close to the -10% that we document from the experiment.

Participation in non-agriculture and the market for hired labor at land-preparation. The calibration does not target market participation. Despite this feature, the model correctly generates the participation in the market for hired labor across farmers with different endowments. The model fails to predict the lack of participation in non-agriculture. While engagement in non-agriculture is stronger for those that report non-agricultural income in the data, engagement is not zero for the reminder farmers. It is possible that the observed lack of participation in non-agriculture is related to other frictions in the labor market which we do not model, including search frictions.

6.1.2 Parameters of Independent Interest

Before discussing the implications of the experiment for welfare we detour to discuss two parameters that might be of interest for the study of mechanization subsidies at scale. The first one is the return to capital and the second one is the shadow value of family labor in the farm.

Returns to Capital. The production structure of the model yields

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

[34] This feature is consistent with the fact that most weeding labor is hired labor.

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) 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 farm in our control group:

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

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

Identification relies on 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, we model a gap between the marginal product of capital and the rental rate as $\tau \in (0, +\infty)$,

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

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 moments pining down the mechanization threshold are independent of the distortion. However, the distortion affects the mapping between capital expenses and the marginal return to capital. We calibrate the wedge τ so that shadow value of family labor on the farm equals their outside option in non-

[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.

agriculture (5% above the wage of the base group, yielding ₹372). We obtain a wedge between the rental rate for capital and the marginal product of capital of 15% $\tau = 0.85$, which yields a return to capital α of 17.7% (see Appendix D.2). This estimate indicates that the marginal product of capital is above its market value, suggesting that farmers could benefit from additional capital services.

Our estimate of the return to capital could also 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 to treatment (with a loading equal to its factor share). As an extreme, assume that all profits are accrued to land returns, i.e. no return to family labor. The mechanization threshold increases slightly above the baseline and the returns to capital are effectively the same as in the baseline.

Family Compensation. To compute the shadow value of family labor we exploit the optimality condition with respect to family engagement in the farm

$$w_f = \alpha(1 - M)\frac{Y}{n_f^P + n^P}.$$

The implied wage per day for family workers in the farm is ₹321, 10% below the market wage for our base group male workers in the farm at land-preparation (₹355), see Table 29. This differential is a symptom of the contracting frictions that tie family workers to their farm.

7 Quantifying Heterogeneity in Welfare.

We first study the implications of the experiment for welfare for the average farmer in the economy, and then highlight heterogeneous responses across farmers. We conclude with an accounting of the sources of productivity gains from adoption of mechanization.

Preferences are logarithmic and separable in consumption and leisure in each stage, $U(c_i^j, n_{il}^j) = \ln(c_i^j) + \ln(n_{il}^j)$. Let the net present value of 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.[36] Define the level of

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

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 the average farm would have required 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, $\gamma_{W,nl}$.

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

The consumption-equivalent welfare from the intervention is 7.6% over the season, as shown in Table 11.[37] If we abstract from the change in leisure associated with the equilibrium response of labor to the subsidy, the consumption-equivalent welfare is about a third, 2.2%. In other words, more than two thirds of the welfare gains from the intervention are accounted for shifts in leisure due to changes in households' labor supply. Aggregation fails in our economy, yet the welfare gains for the average farm are almost identical to the ones estimated for the aggregate (7.61% vs. 7.6%). However, the gains accrued to consumption for the average farm are almost twice of those implied by aggregate welfare (3.9% vs. 2.2.%). These disparities highlight the importance of studying the heterogeneous welfare effects of the intervention.

To study heterogeneity, Table 11 reports welfare changes for farmers with different time and land endowments, as well as supervision ability. The aggre-

[37] We have abstracted from the cost of the intervention in assessing these gains. If we tax farming households lump-sum by the size of the subsidy, the welfare gains are 0.6p.p. lower than the benchmark.

Table 11: Welfare

	(a)	(b)	(c)	(d)	(e)	(f)
Hires at land-prep	✓	✓			Aggregate	average
Non-agricultural income		✓		✓	γ	$\bar{\gamma}$
(1) Total, γ_W	7.2%	7.3%	8.5%	6.4%	7.6%	7.6%
(1.b) Farm TFP improvement	2.6%	2.6%	5.4%	4.9%	3.4%	2.6%
(2) Only consumption, γ_{W,n_l}	3.7%	3.8%	-2.0%	-1.7%	2.2%	3.9%
(2.b) Farm TFP improvement	1.2%	1.2%	2.7%	2.8%	1.6%	1.2%

Welfare measures for different population of farmers, Column (a)-(d); the aggregate measure discussed in the text is in Column (e) while welfare for the average farmer is in Column (f) . Row (1) is the overall effect of the intervention and row (1.b) singles out the contribution of the shift in endogenous TFP to treatment. Row (2) is the welfare gains from changes in consumption only while row (2.b) singles out the contribution of the endogenous TFP.

gate and average welfare effects are similar to those of the population of farmers that hire workers, which is not surprising given that they represent more than 70% of the population. Interestingly, the welfare gains for those that do no hire labor at land-preparation (i.e. that have lower supervision ability) are disproportionally accounted for by improvements in leisure. For this set of farmers, a measure of welfare based on consumption would predict welfare losses from higher mechanization. Yet the contribution of productivity shifts to welfare is positive across all farmers, with stronger effects for those that do not hire labor at land-preparation. The reason is that farmers with low supervision ability disproportionally benefit from a decline in the measure of tasks that need to be performed by hired labor at harvest. At the same time, the heterogeneity in the contribution of TFP across farmers also shows that most of the welfare gains for those with high supervision ability stem from capital-deepening, consistently with their relatively low capital-labor ratios at baseline.

7.1 The total factor productivity effect

Shifts in total factor productivity contribute about half of welfare gains from the intervention. Here we discuss the magnitude of the productivity change as well as its relative importance for movements in output per acre vis a vis the direct effect of capital intensification. An empirical measure of the elasticity of total factor productivity to treatment ϵ_A can be computed residually from the

characterization of the elasticity of output per acre to treatment,

$$\epsilon_{\frac{y}{l}} = \underbrace{\epsilon_A}_{productivity} + \underbrace{(\alpha M)\epsilon_{\frac{k}{l}}}_{intensive-mech} \underbrace{- \alpha M \ln(\frac{k}{n_f^P + n^P})\epsilon_M}_{extensive-mech} + \underbrace{\alpha(1-M)\epsilon_{n_f^P+n^P} + \alpha_f^H \epsilon_{n_f^H} + \alpha^H \epsilon_{n^H}}_{labor-replacement}. \tag{9}$$

There are two challenges in computing this elasticity. First, such a residual is a function of the return to family labor which is unobserved; and second, it depends on the elasticity of family *productive* labor in the farm in both processes, also unobservable. As described in the calibration, we measure the return to family labor as a residual from the share of capital, hired labor and land, under the assumption of constant returns. We also exploit our detailed task data and adjust family working days at each stage with the working days reported by the household head, who disproportionally engages in supervision activities. Finally, the computation of the elasticity requires a measure of the change in the mechanization threshold, which we obtain differentiating equation 6, $\epsilon_M = \frac{1-M}{\beta}\epsilon_{k/(n_f^P+n^P)}$.

Equation 9 highlights the key channels through which mechanization affects revenue per acre. The first one is the *productivity* term which we measure residually. 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 because there are less workers in the farm when the cost of capital falls. The sign of the productivity effect could be positive or negative.

Table 12 reports our findings for the relative strength of each channel explaining changes in revenue per acre. We find that the effect of more intensive mechanization, i.e. more capital, is stronger than the extensive mechanization effect, i.e. a larger share of tasks performed by capital. The labor replacement channel account for the bulk in the movement in output per worker and is posi-

Table 12: Productivity Decomposition, channels (percentage points)

Revenue per acre	Intensive mechanization	Extensive mechanization	Labor Replacement	Total	TFP
(1)	(2)	(3)	(4)	-(2)+(3)+(4)	-(2)+(3)+(4)+(1)
A. Benchmark, frictionless capital markets					
0.0	0.8	0.01	3.6	2.8	2.8
B. Frictions in capital markets, $MPK\tau = r$.					
0.0	0.9	0.01	3.2	2.3	2.3
C. Higher land share, $\alpha_l = 0.18$.					
0.0	0.8	0.0	1.7	0.9	0.9

Each element of the table computes different channels through which a subsidy on mechanization affects revenue per acre, as characterized in equation 9. Panel A. is our benchmark, Panel B. allows for frictions in capital rental markets, and Panel C. increases the share of land to 18% as in Valentinyi and Herrendorf (2008).

tive at 3.6p.p.. Overall, we find that the elasticity of total factor productivity to treatment is 2.3p.p. in our baseline calibrated economy.

If instead we compute the total factor productivity for the economy with a wedge in capital rental markets, the implied productivity improvement is slightly smaller at 2.3p.p, mostly due to a weaker labor replacement effect. 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. 18% as estimated by Valentinyi and Herrendorf (2008). We adjust the return to family labor so that overall profitability in the farm remains constant. The estimated productivity gains are the smallest here at 0.9p.p. consistent with a weaker labor replacement effect in response to a lower share of family labor, and a stronger intensive margin effect.

In conclusion, productivity gains from the intervention were 2.8% in the baseline economy, and can be as low as 0.9% if the return to family labor is lower than under the baseline calibration. The observed null effect on output per worker is due to the counteracting effect of the labor replacement channel.

8 Conclusion

We provide the first causal estimates of the returns to mechanization. Our structural estimates suggest productivity improvements in farming and welfare gains that stem mostly from higher leisure. Mechanization impacts labor use in the farm in a nuanced way due to task specialization by different types of labor, and welfare gains from the intervention are heterogeneous across farmers with different engagement in the non-agricultural and hired labor markets.

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. 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.[38] 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.

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

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A Additional Tables

Table 13: 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 14: 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 15: 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 16: Most Commonly Rented Implements

Commonly Rented Implements- Control Group	(1) N	(2) Mean	(3) 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 17: Mechanization Index Treatment Effects by Voucher

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

Standard errors clustered at the village-level in parentheses.

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

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

Table 18: 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 19: 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 20: Mechanization Index Treatment Effects by Voucher

	(1) IHS(Mechanization Index)	(2) 1(Matched) 1(to Platform)
1050 Subsidy	-0.00194	0.262****
	(0.0857)	(0.0315)
1050 Subsidy, 1050 Cash	-0.0110	0.100****
	(0.0709)	(0.0274)
2100 Subsidy	0.114**	0.316****
	(0.0474)	(0.0218)
2100 Subsidy, 1050 Cash	0.0376	0.336****
	(0.0440)	(0.0249)
1750 Subsidy	0.169**	0.350****
	(0.0819)	(0.0478)
1750 Subsidy, 1750 Cash	0.153**	0.124***
	(0.0715)	(0.0427)
3500 Subsidy	0.0775	0.459****
	(0.0476)	(0.0361)
3500 Subsidy, 1750 Cash	0.130*	0.436****
	(0.0675)	(0.0422)
1(Large Farmer)	0.458****	0.0199
	(0.0337)	(0.0123)
Constant	-0.167****	0.108****
	(0.0171)	(0.00863)
Control Mean	-0.0500	0.100
Observations	4989	5399
1050 Subsidy=1750 Subsidy	0.136	0.124
1050 Subsidy, 1050 Cash=1750 Subsidy, 1750 Cash	0.0708	0.600
2100 Subsidy=3500 Subsidy	0.543	0.0000556
2100 Subsidy, 1050 Cash=3500 Subsidy, 1750 Cash	0.212	0.0215

Standard errors clustered at the village-level in parentheses.

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

Table 21: Binary for Labor Use: Treatment Effects

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

Standard errors clustered at the village-level in parentheses.

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

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

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

Table 22: Number of Workers During: Treatment Effects

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

Standard errors clustered at the village-level in parentheses.

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

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

Table 23: Hired Worker per Supervising Family Member, 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 24: Tasks First Listed Being Performed by Types of Labor

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

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

Table 25: Crop Choice Treatment Effects

	(1) 1(Paddy Grown)	(2) 1(Maize Grown)	(3) 1(Cotton Grown)
Cash and Mechanization	0.00494	0.00839	-0.00676
	(0.0144)	(0.0143)	(0.00882)
1(Mechanization)	-0.00388	-0.000826	0.00975
	(0.0120)	(0.0122)	(0.00751)
Control Mean	0.210	0.160	0.210
Observations	5035	5035	5035

Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
1(Paddy Grown) is a binary variable that takes the value 1 if the farmer grows paddy and 0 otherwise.
1(Maize Grown) is a binary variable that takes the value 1 if the farmer grows maize and 0 otherwise.
1(Cotton Grown) is a binary variable that takes the value 1 if the farmer grows cotton and 0 otherwise.

Table 26: Output Per Acre: Treatment Effects

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

Standard errors clustered at the village-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$
1(Output Sold) is a binary variable that takes the value 1 if the farmer reported selling input, and 0 otherwise.
Proportion Sold is the proportion of output sold. IHS(Profit/Acre) is the money left over from farming reported by the farmer. IHS(Revenue/Acre) is the sum of expenses and profits.

Table 27: 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 28: 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 29: 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.

B Proofs

B.1 Allocations

Preparation stage The optimality conditions for inputs across tasks are

$$p(m)a_n(m) = w + \frac{\omega}{\phi_i} w_{if}^P, \tag{10}$$

$$p(m)a_n(m) = w_{if}^P, \tag{11}$$

$$p(m)a_k(m) = r, \tag{12}$$

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

Optimality conditions for tasks

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

The optimality conditions with respect to input intake are

$$\alpha(1 - M_i)\frac{y_i}{n_{if}^P + n_i^P} = w_{if}^P \qquad \text{if } n_{if}^P > 0, \tag{13}$$

$$\alpha(1 - M_i)\frac{y_i}{n_{if}^P + n_i^P} = w + \frac{\omega}{\phi_i} w_{if}^P \quad \text{if } n_i^P > 0, \tag{14}$$

$$\alpha M_i \frac{y_i}{k_i} = r. \tag{15}$$

Harvesting stage

Optimality conditions for tasks

$$\alpha_f^H y^H = p(m)n_{if}^H(m)$$

$$\alpha^H y^H = p(m)n_i^H(m)$$

and the linearity of labor in tasks implies,

$$b_f(M_i)\alpha_f^H \frac{y_i}{n_{if}^H} = w_{if}^H, \tag{16}$$

$$b(M_i)\alpha^H \frac{y_i}{n_i^H} = w + \frac{\omega}{\phi_i} w_{if}^H. \tag{17}$$

B.2 Mechanization Thresholds

Proposition 1 (proof). 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 4 and table 8.[39]

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, $w_{if} = w_o < \frac{w}{1-\frac{\omega}{\phi_i}}$. 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 4 and 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 4 implies that the mechanization threshold is independent of land and time endowments given 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 conditions for goods and time and jointly with the mechanization threshold that follows from equation 4.

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

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

   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.

□

[39] 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 for 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. Capital-labor ratios are the same across farmers that hire workers irrespective of their engagement in non-agriculture. Also, there are not differences in total supervision to working days across these households, suggesting no differential ability across them, ϕ.

C Experimental findings through the lens of the model

In what follows, we focus on the behavior of the average farm and interpret the intervention with the shift in capital-labor ratios observed in the data. Let the mechanization threshold for the average farm be M and normalize the supervision ability of the average farm to 1, $\phi = 1$. 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.

$$\frac{\tilde{w}}{r} = \frac{k}{n_f + n^P} \frac{1 - M}{M} \tag{18}$$

The strength of the second channel depends on the bias of technology:

$$\frac{a_n(M)}{a_k(M)} = \frac{k}{n_f + n^P} \frac{1 - M}{M} \tag{19}$$

Therefore, when capital is subsidized and capital labor ratios raise, the share of mechanized tasks 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 18, either because farming hours are replaced by machine-hours, or because hired labor falls and with it, family supervision time.

Fact 2.b *Family labor falls at harvesting* Optimality requires that family labor is proportional in both processes (see B.1). An increase in the mechanization threshold, increases the marginal product of labor at the harvesting stage. This effect is counteracted by a substitution effect at land-preparation that lowers labor demand. 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. Finally, family labor is in part devoted to worker supervision, so lower demand for hired labor also induces lower family labor at harvesting.

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 to each other at the harvesting stage. Therefore, if wages for hired workers and family labor do not change, labor hired declines proportionally to family labor.[40] If in addition, the set of tasks at harvesting fall in response to stronger mechanization at land-preparation, $\frac{\partial b(M)}{\partial M} < 0$, the demand for labor declines even further.

Fact 4 *Revenue per acre does not increase on average* This result follows from the ambiguous sign of the elasticity of total factor productivity to treatment, equation 9.

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 6.1.1, 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.

D 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.[41]
- 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

[40] 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 6.1, is predicted to increase by 0.7p.p.. Absent changes in labor productivity at harvesting, the calibrated economy predicts that the ratio of hired to family labor at harvest declines by 7p.p. in response to treatment, and therefore that hired labor falls more than family labor.

[41] Average expenses by stage as reported in Table 28 are slightly higher than the implied ones following our methodology.

family labor supply to the farm to construct a measure of family productive labor. The baseline results substract their engagement at the preparation stage.[42]

D.1 Labor Decisions

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

The optimal time allocation by the household satisfies,

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

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

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

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

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

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

Whether hired labor is positive or not depends on the marginal product of labor,

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

which scales of farming productivity, and the size of the family through the available working time, $\bar{n}$.

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

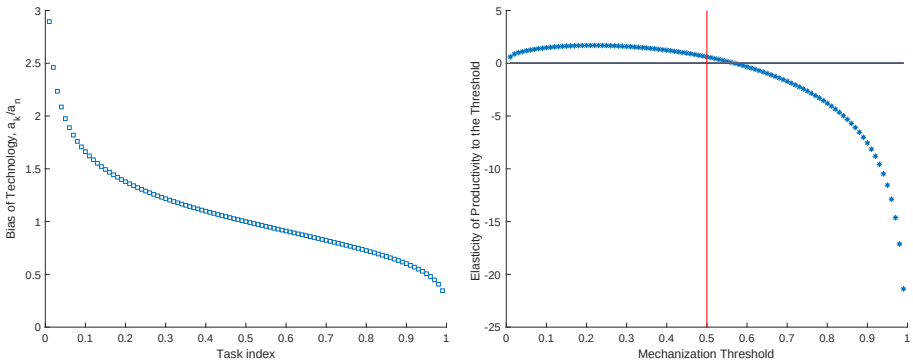
$$n_f = \left(\frac{\gamma Z}{w_o}\right)^{\frac{1}{1-\gamma}}$$

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

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

D.2 Calibration

Figure 1: Calibrated profile.



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

Table 30: Returns

αM	$\alpha(1-M)$	α_l	α_f^H	α^H	M	α
Baseline, frictionless capital markets						
8.0	8.0	4.9	18.6	60.6	0.5	15.9
Frictions, $MPK\tau = r$ for $\tau = 0.85$						
9.3	9.3	4.9	15.9	60.1	0.5	18.6
No return to family labor, $\alpha_l = \frac{\pi}{y} = 0.23$						
8.0	7.6	23.5	0	60.6	0.50	15.9

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.