Gender and Mechanization: Evidence from Indian Agriculture

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Abstract

Technological change in production processes with gendered division of labor across tasks, such as agriculture, can have a differential impact on women's and men's labor. Using exogenous variation in the extent of loamy soil, which is more amenable to deep tillage than clayey soil and therefore more likely to see adoption of tractor driven equipment for primary tilling, we show that mechanization led to significantly greater decline in women's than men's labor on Indian farms during 1999-2011. Reduced demand for labor in weeding, a task often undertaken by women, explains our findings. The estimates suggest that a 10% increase in mechanized tilling led to a 5% fall in women's farm labor use, with no accompanying increase in their non-farm sector employment. Our results highlight the gendered impact of technological change in contexts where there is task based gender division of labor with limited opportunities for women to diversify their workforce participation.

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Existing literature has focused on the effects of technological change on skilled versus unskilled labor when they are imperfect substitutes and technology complements skilled labor (Acemoglu and Autor, 2011). However, there is limited evidence of the impact of technological change in contexts where the division of labor across tasks is gendered, leading to imperfect substitutability between male and female labor, for instance in agricultural production (Skoufias, 1993; Doss, 1999; Qian, 2008; Mahajan and Ramaswami, 2017). While mechanization is often labor substituting (Pingali, 2007; Cossar, 2019; Caunedo and Kala, 2021), insights into whether and how mechanization affects women's and men's labor differentially is missing.

Technological change, in general, and agricultural mechanization, in particular, is unlikely to affect male and female labor equally, since men and women are not only imperfect substitutes but their degree of complementarity with machinery also differs (Boserup, 1970; Laufer, 1985) in agricultural production. For instance, women perform agricultural tasks such as weeding and transplanting which require different skills, and which have limited substitutability with the tasks typically performed by men, such as tilling. Moreover, men are more likely to operate and maintain machinery, e.g. tractors (Brandtzaeg, 1979).

In this paper we use data on farm labor and input usage during 1999-2011 in India - a period of rapid agricultural mechanization - to analyse the effect of increased use of farm machinery on men's and women's labor use in agriculture. During this period, the number of tractors in India tripled - from 2 to 6 million (Bhattarai et al., 2016), increasing the intensity of tractor usage on Indian farms from 16 to about 40 per 1000 hectare - an indicator of the extent of mechanization since tractors provide power to most farm based machine tools.[1] At the same time, the proportion of working age adults employed in rural farm sector fell by 12 percentage points (National Sample Survey 1999 and 2011). Women have fared worse, with not only a decline in their farm sector employment but also a steady decline in their overall work force participation in rural India over the last three decades (Afridi et al., 2018) - from 47% in 1999 to 37% in 2011 and further to 26% in 2017 (Periodic Labor Force Survey, 2017). A large part of this decline was due to a reduction in women's employment in agriculture with no commensurate increase in their employment in other sectors.[2]

We exploit exogenous variation in agricultural machinery usage due to the difference in the share of loamy versus clayey soil texture in districts within Indian states. Our results show that machine usage in tilling of land is significantly higher in districts with relatively more loamy soil. This is in line with literature that shows deep tilling is more amenable in loamy than clayey soils (Wildman, 1981; Bigot et al., 1987). We then utilize this predicted, exogenous variation in mechanization in the first stage to analyse its impact on the number of men and women employed per hectare of cultivated land (henceforth, labor use) in a 2SLS specification. We find that that a 10% increase in mechanization leads to a 5% fall in women's farm labor use, an elasticity of almost half. These empirical results are supported by a simple theoretical model we construct, in which male and female labor are considered separate inputs in agricultural production. We show that technological change can not only reduce labor use, but that it can have a differential impact by gender when men and women are imperfect substitutes and their relative weightage in the production process differs.

Further, our analysis indicates that greater machine use in tilling operation can impact demand for men's and women's labor not only in the operation undergoing mechanization but also in downstream operations. The estimated decline in women's labor is driven by a significant fall in labor used for weeding, an operation that follows tilling of land in the agricultural production process. With greater mechanization in tilling, a task where more male vis-a-vis female labor is used in Indian agriculture, it is possible that demand for male labor falls. However, to the extent that men's labor is complementary to tilling machines since they are more likely to operate, maintain or monitor these machines than women, any fall in men's labor usage may be mitigated. On the other hand, better quality tillage reduces weed growth, lowering the demand for weeding labor - a task that has traditionally been performed by women across agricultural systems. Hence, the overall effect of mechanization on women's labor use is significantly more adverse than men's. At the same time, we do not find evidence of substitution of women's labor towards the non-farm sector, suggesting either lack of alternative employment opportunities or limited physical mobility of women or both. Our results are robust to a host of controls for agricultural, demographic and economic characteristics of a district, including pre-existing labor force participation of women, state specific factors and district specific employment trends due to differences in initial labor use.

Previous research has looked at technological innovations in agriculture, mostly brought about by the advent of the green revolution in developing countries (Foster and Rosenzweig, 1996), considering labor as a homogeneous entity (Pingali, 2012). More recently, research on improved seed varieties (Bustos et al., 2016; Emerick et al., 2016), increased fertilizer (Beaman et al., 2013) and irrigation (Asher et al., 2021) finds a positive impact on labor use due to increased productivity. On the other hand, the literature that looks at technological changes brought by agricultural mechanization in power-intensive operations like tilling and harvesting (other than irrigation) has largely found a reduction or no effect on labor use depending on complementarity between labor and machines (Hamilton et al., 2021). For instance, in a review of 24 studies examining the effect of mechanization in agriculture on labor use, Norman et al. (1988) find that all, except two, report lower labor use for farms which used tractors as opposed to draft animals. Twelve of these studies report reduction in labor use by 50% or more. Verma (2006) looks at the findings of more than 15 studies and reports that either labor use or animal power per hectare decreases with use of tractors on Indian farms. The effect on total farm labor, however, is often ambiguous and depends on the productivity impacts of mechanization. If farm productivity increases simultaneously with mechanization then total farm labor use may also rise to the extent that yield and multiple cropping increase. However, evidence of increase in yields or acreage due to the adoption of power-intensive mechanization, such as tractors, is mixed and largely depends on whether it improves tilling quality (Pingali, 2007).

More recently, Cossar (2019) examines the impact of increased adoption of tractors on labor use in Ghana. It finds an insignificant impact on tilling labor use while there is an increase in labor use in other operations due to increased productivity. Further, the study finds no gender differentiated impacts in Ghana, where men and women cultivate separate plots of land - a context very different from South Asia. In contrast, Caunedo and Kala (2021) show that providing vouchers for hiring of agricultural machinery in India increases hours of farm machinery usage across operations and reduces labor use with an elasticity of almost one. Women's hired labor use declines with no effect on male labor.

Our study contributes to several strands of research. First, and more broadly, it furthers our understanding of how technological change in a production process, where there is gender-based specialization of labor, can have heterogeneous effects on men's and women's labor use. Second, it aids our understanding of how structural transformation induced by technological change in agriculture (where women an an average comprise 43% of the labor force in developing countries (Quisumbing et al., 2014)) can potentially exacerbate existing gender inequities in labor force participation. The gendered effects of mechanization on labor likely depend both on the types of tasks that are mechanized and its spillover impact on complementary tasks. Finally, and more narrowly, this study broadens our understanding of the potential reasons for the decline in women's workforce participation in India, a topic of fierce debate but limited consensus, in recent years. In contrast to existing research that has focused on supply side factors, such as an increase in women's education, household incomes, home productivity and social norms (e.g. Afridi et al. (2018, 2019)), we highlight the channel of labor demand and its effect on women's labor force engagement.

The remainder of the paper is organized as follows. We first describe the nature of the production process in Indian agriculture (Section 2) followed by a simple theoretical model that conceptualizes the potential gender impacts of technological change on the farm (Section 3). Section 4.1 describes the data sets used and the construction of our variables of interest. The empirical strategy is outlined in Section 4.2 while our findings and their robustness are presented in Section 5. We discuss the mechanism that explains our results and the implications of our findings in Section 6. Section 7 concludes.

Background

Agricultural operations can be broadly classified into three stages: Stage 1 - land preparation involving primary and secondary tilling; Stage 2 - sowing and intercultural operations like weeding; and Stage 3 - harvesting and threshing. Given this nature of the production process, there exist complementarities across operations in agriculture.

Three characteristics of the production process need to be highlighted, since these carry implications for gender differentiated impacts of mechanization - a change in the source of power used in an operation, from simple hand tools and animal draught power to mechanical power. First, the extent of physical strength vis-a-vis precision or control required to perform an operation primarily determines the degree of mechanization of that operation in agricultural production (Norman et al., 1988). The most power or strength intensive operation is primary (or deep) tilling, followed by secondary (or shallow) tilling. Existing evidence, thus, indicates that Stage 1 operations are typically more likely (and the first) to be mechanized (Pingali, 2007). Mechanization in Stage 1 is often followed by increased use of machinery in downstream tasks, particularly for Stage 3 harvesting operations. Stage 2 operations require less physical strength and more precision, thus are usually less likely (or the last) to be mechanized. This pattern for adoption of mechanization in agriculture has been observed for both developed as well as developing countries (Binswanger, 1986; Pingali and Hossain, 1998; Singh, 2015).

In general, adoption of machines can either displace or augment labor use per hectare depending on the operation for which they are used and their impact on agricultural productivity.[3] In this paper we specifically look at mechanization in Stage 1 of the agricultural operations, i.e. tilling. In this operation, the ploughing implements for both primary and secondary tilling are driven by either a tractor or a power tiller.[4] Therefore, it is likely that usage of ploughing implements for secondary tilling operation is linked to adoption of ploughing implements in primary tilling operation, since the largest fixed cost of mechanization involves tractor purchase.[5] On the other hand, harvesting implements are primarily self propelled machines (except combine harvesters that trail behind tractors and constitute no more than

10% of total mechanical harvesting equipment in India (Input Census)). Sowing and weeding, relatively more precision based operations, often show low uptake of mechanized implements.

The second relevant feature is that the extent of machine uptake in tilling depends on the depth of required tillage. The tillage depth in turn is affected by loamy versus clayey content of soil in a region (Müller and Schindler, 1999). Loamy soils are more amenable to deep tilling (Bigot et al., 1987; Wildman, 1981), which requires at least 45 cm of soil to be turned over (Dunker et al., 1994). Increasing clay content in soil only allows for secondary tillage. Notably, the total power requirement depends on tillage depth and soil resistance, which are inversely related. Thus, areas with more loamy soil content are more likely to use deep tilling/ploughing machines due to greater tilling depth requirement (Carranza, 2014). The loam content of the soil relative to clay could, therefore, affect the adoption of power operated machines, specifically in tilling.

The third and final relevant characteristic is the gendered division of labor in agriculture - men and women perform different tasks. They are, hence, imperfect substitutes for each other in agricultural production (Burton and White, 1984; Jacoby, 1991; Skoufias, 1993; FAO, 2011). Existing evidence shows that women's labor is less likely to be used in operations that require physical strength, e.g. Stage 1 tilling operations, and more likely to be utilized in tasks that require precision, e.g. in general Stage 2 operations, viz. sowing/transplanting and weeding (Bardhan, 1974; Mahajan and Ramaswami, 2017) and for picking tea leaves in tea cultivation (Qian, 2008). Indeed, operation level data from National Sample Surveys of India shows that out of the total labor used in a given task, female labor constituted less than 10% in Stage 1 tilling operation but over 32% in sowing and weeding during 1999-2011 (Table 1).

The above discussion highlights the potential impact of technology adoption on labor use not just in the specific operation that gets mechanized but also in other operations due to the complementary nature of production. For instance, if machines improve soil tillage in Stage 1 then less weeding, and thereby less labor is required in Stage 2. Thus, an increased uptake of machines in tilling can have direct and indirect effects on labor use. The direct effects can occur through substitution of labor used in tilling with the machinery while improvement in tilling quality due to machine adoption can indirectly lower the demand for labor in other tasks, viz. weeding (FAO). It is, therefore, imperative to analyse the impact of technological change on overall labor use as well as by operation, for men and women.

In the next section, we use a simple theoretical model to conceptualize the potential effects of mechanization on labor use in agriculture by gender.

Theoretical model

We model an agricultural sector where the final good (Y) is produced using two inputs, namely aggregate labor (L) and aggregate land (T). The total labor L is composed of female labor (F) and male labor (M). We denote the wages of female and male labor by w_F and w_M, respectively, and the factor price of land by R. The market price of the final agricultural product Y is represented by P.

We assume that the production of the final good follows a Constant Elasticity of Substitution (CES) technology of the following form:

$$(1) \qquad Y(L,T) = A_a[\theta(A_L L)^{\frac{(\sigma-1)}{\sigma}} + (1-\theta)(A_K T)^{\frac{(\sigma-1)}{\sigma}}]^{\frac{\sigma}{(\sigma-1)}}.$$

Here, A_a represents Hicks-neutral technological change, A_L and A_K represent labor-augmenting and land-augmenting technological change, respectively. The parameter $\sigma > 0$ measures the elasticity of substitution between labor and land and the relative importance of these two factors of production is given by $\theta \in (0,1)$. Throughout the analysis we have assumed that labor and land are complementary to each other, i.e. $\sigma < 1$, in the agriculture production process (see for example, Bustos et al. (2016)).

Since agricultural operations are gender specific, aggregate labor L is assumed to combine

F and M in the following way:

$$L(F, M) = [\alpha F^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha) M^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{\epsilon}{(\epsilon-1)}}. \tag{2}$$

The elasticity of substitution between female and male labor is represented by $\epsilon > 0$ and their relative importance is denoted by the parameter $\alpha \in (0, 1)$.[6] Further, for our purpose, we assume that the weight given to male labor in the production function $(1 - \alpha)$ is more than half. That is, while aggregating labor in the production process the relative importance of male labor is higher than that of female.

Agricultural sector is assumed to be competitive in nature and therefore profit maximizing farmers would engage an input up till the point where the value of the marginal product of that input equals the factor price.[7] Given the setup, the profit maximizing conditions with respect to the three factors, F, M and T are as follows:

$$P\frac{\partial Y}{\partial F} = w_f, \quad P\frac{\partial Y}{\partial M} = w_m, \quad P\frac{\partial Y}{\partial T} = R. \tag{3}$$

Empirically, there exists a gender difference in the wage rate in agricultural labor markets (Lagakos and Waugh, 2013), which also holds in the Indian context (Mahajan and Ramaswami, 2017). Therefore, for our main results we focus on the case when male wage (w_m) is higher than for female labor (w_f).

In this fairly general framework, to examine the effect of mechanization on the labor use, we assume a Hicks neutral productivity change due to mechanization since machine use can plausibly increase the productivity of both labor and land. We derive the conditions under which mechanization of the production process, i.e. a change in A_a, can decrease labor use per hectare and crucially, have a gender differential effect. Given these fairly reasonable assumptions, we derive the proposition that shows the conditions under which female to male labor intensity decreases with the technological shock along with a decline in labor use for each gender (see Proposition B.1 and the associated proof in online Appendix B). The proposition holds for a set of values of the elasticity of substitution between male and female labor, ϵ, where the lower bound is less than or equal to one (but not zero) and the upper bound is greater than one (but not infinity) i.e. when male and female labor are neither perfect substitutes nor perfect complements.[8]

Intuitively, even when male wage is higher than the female wage, if the weightage of male labor is larger in the production process and men and women can be replaced with each other but not perfectly, the sector is likely to see a smaller fall in the use of male than female labor when technological change occurs.

Data and Methodology

We focus on India's agricultural sector during 1999-2011 for two reasons. First, this period saw a much larger increase in mechanical power in Indian agriculture as compared to previous decades.[9] Second, 1999-2011 witnessed a significant decline in rural women's labor force participation (Afridi et al., 2018).[10]

Data

We compile information from multiple sources over time (1999, 2007, 2011) on farm employment, agricultural inputs, climate and socio-economic characteristics at the district level in India to create a dataset with 1077 district-year observations.[11] Construction of our main variables of interest and the data sources is briefly described below (See online Data Appendix C for more details).

Farm Labor Use: We utilize data on employment in the farm sector in rural India from the nationally representative National Sample Surveys (NSS) of India for three rounds - 55^{th} (1999), 64^{th} (2007) and 68^{th} (2011). These surveys capture the entire agricultural year in each district, and thus cover all seasons. Our main outcome of interest is the number of workers per hectare of cultivated land in a district, by gender. It is obtained by dividing the estimated number of individuals in the working age group (15-65 years) of that gender engaged in farm cultivation in a district by the total cultivated area (from the Input Census) in that district in that year, henceforth 'labor use'. This measure, standard in the literature on the effects of mechanization on labor use (Pingali, 2007), normalizes the total labor use by cultivated area since cultivated area is likely to be endogenous.

We also disaggregate agricultural employment by operation (tilling, sowing, weeding, harvesting and others). For this, we make use of the weekly employment data (the number of days worked in the week preceding the survey date) in the NSS surveys since the information on agricultural tasks is captured only at weekly frequency. We calculate the total number of workdays in a week that workers are engaged in the given agricultural operation per hectare of cultivated land in a district, by gender.[12]

Farm Mechanization: Information on the intensity of agricultural mechanization at the district level is compiled from three Input Census rounds, conducted once every five years by the Ministry of Agriculture in India: 1997-99, 2006-07 and 2011-12, referred to as 1999, 2007 and 2011 (the latest year for which district level data are available), respectively.[13] These rounds correspond most closely to the employment data discussed above.

The Input Census gives the area cultivated under each of the implements in that agricultural year. First, we classify implements based on the source of power - hand, animal and power operated - and by type of operation.[14] Specifically, power operated implements are those which require electrical or mechanical source for drawing power and thus correspond to machine uptake in agriculture. Next, we aggregate the area cultivated under all the implements for a given source of power - overall and by the type of agricultural operation. We then divide this aggregated area by total area under cultivation in that agricultural year in the district to calculate the intensity of usage of implements for a given source of energy and also by operation. We define mechanization as the percentage area cultivated under mechanical power operated primary and secondary tilling equipment.[15]

Soil Characteristics: The National Bureau of Soil Survey (NBSS) classifies soil texture into three categories - loamy, clayey and sandy - which are aggregated over 13 textural classes based on the system followed by the United States Department of Agriculture (USDA).[16] Besides soil texture, data on other soil characteristics such as soil depth, pH and slope are also available that can directly affect soil fertility and labor use. We digitized the publicly available NBSS soil maps (designed during the mid 1990s for various states of India) using Geographic Information System (GIS). We then overlaid the district boundaries on the digitized maps to obtain district-level soil characteristics, by summing up the area in a district having a particular soil characteristic and dividing it by the total area of the district. This gives us the proportion of area in a district that is loamy, clayey or sandy, besides other soil characteristics. We then construct our measure of 'loaminess' as the difference between the share of loamy and clayey soil in a district, which is likely to influence the required depth of tillage and thereby take-up of machinery in the agricultural operation of tilling.

Other District Characteristics: We compile data for a host of other district level agricultural characteristics that can impact both agricultural mechanization and labor use (e.g. climate, irrigation, demographic details (urban, religion, caste, education), average landholding size, crop composition, development levels (road accessibility and nightlights) and fertilizer usage) using the NSS rounds, the decennial Census (2001 and 2011), data from Ministry of Agriculture, Defence Meteorological Satellite Program (DMSP; 1992-2013) and Fertilizer Association of India.

Table 2 shows the summary statistics for farm employment and mechanization for each year in our analyses.[17] Clearly, female labor use has fallen over time and male labor use has not changed much during 1999-2011. Figure 1(a) plots the change over time by indexing the labor use in each year by the labor use in year 1999 for that category, reflecting the trends in farm labor use by gender as seen in the summary statistics. We observe a secular fall in female labor use over time, while male labor use has not fallen but rather plateaued in recent years.

The above trend in farm labor use has been accompanied by a rise in agricultural mechanization in India. Table 2 shows that our measure of farm mechanization (for tilling operation) has increased from 18.6 in 1999 to 50.4 in 2011, which is a 32 percentage point increase during 1999-2011. Figure 1(b) plots the change over time for dis-aggregated implement usage by different sources of power (for all operations). The usage of implements for a particular source of power in each year is indexed by its usage in the year 1999. We see an increase in implements drawn by mechanized sources of power during 1999-2011, while those operated using human power and animal power declined. Further, Figure 2 shows the change in implement usage for each source of power dis-aggregated by the agricultural operation for which it is used. The largest increase in use of mechanical power occurred in the tilling operations (Stage 1), followed by harvesting and threshing (Stage 3). Sowing and weeding operations (Stage 2) did not see any significant mechanization in India during this period.

The above evidence indicates that while agriculture labor use has been falling over time, especially for women, farm mechanization has been rising.[18]

Empirical Strategy

In order to draw a causal link between farm mechanization and agricultural employment we estimate the below specification using the data described above:

$$L^g_{dst} = \beta^g_0 + \beta^g_1 Mechanization_{dst} + X_{dst}\beta^g_3 + D_s + D_t + \epsilon^g_{dst} \tag{4}$$

Here, d refers to district, in state s at time t and the superscript g refers to gender, i.e. either male (M) or female (F) labor. The dependent variable (L) is the inverse hyperbolic sine transformation of the number of male or female workers employed per hectare of cultivated land multiplied by 100.[19]

$Mechanization_{dst}$, our main variable of interest, captures the intensity of machine usage in Stage 1 of agricultural production, i.e. *Tilling*. It is defined as the total area tilled by machines divided by the total area cultivated (multiplied by 100), in district d and year t. Thus our main coefficient of interest, β_1, captures the percentage change in labor use per hectare when intensity of mechanization increases by one percentage point.[20] X_{dst} is a vector of controls for soil characteristics, pre-mechanization (initial) period labor use, agricultural and socio-demographic characteristics, the details of which are discussed later. State fixed effects and time fixed effects are denoted by D_s and D_t, respectively. The regressions are weighted by district population to correct for potential heteroscedasticity when using estimates from survey data as the dependent variable (Wooldridge, 2010). Throughout, the standard errors are clustered at the district level to control for serial correlation in standard errors over time within a district.

Since machine usage is likely to be endogenous to relative factor prices and other economic characteristics of a district, we adopt an instrumental variable (IV) strategy that exploits the linkage between pre-existing soil texture and its effect on tillage requirements as a determinant of adoption of mechanization in tilling operation. In our reduced form analysis, the first stage specification is given as below:

$$Mechanization_{dst} = \pi_0^g + \pi_1^g Loaminess_{ds} + X_{dst}\pi_2^g + D_s + D_t + e_{dst}^g \tag{5}$$

Again, here d refers to district in state s at time t, and the superscript g refers to gender. The variables are as defined above. The instrumental variable *Loaminess* is measured as the difference in the loamy and clayey soil shares in district d of state s. As discussed previously, we hypothesize that uptake of primary and secondary tilling machines, which are attached behind tractors and power-tillers, are likely to be affected positively by greater presence of loamy soil in comparison to clayey soil. We exploit the within state variation in soil texture across districts to rule out any state specific factors which result in greater adoption of machines.[21] The estimates in the second stage should, hence, be interpreted as the local average treatment effect (LATE) of mechanization on labor use across the three years as they capture the average treatment effect on the complier sub-population of districts where higher loaminess led to greater mechanization (Imbens and Angrist, 1994).

Control variables: To meet the IV exclusion restriction, i.e. differences in soil texture do not directly affect women's labor use in farming, we include a host of control variables in our empirical analyses, as follows:[22]

(a) State and year fixed effects (FE): State fixed effects (D_s) control for unobserved, time-invariant, within-state factors that could affect machine uptake and labor use and also be potentially correlated with soil characteristics, e.g. cultural norms around women's work participation (Mahajan and Ramaswami, 2017). Year fixed effects (D_t) account for macroeconomic trends (e.g. rising incomes) common to all districts which could affect both machine uptake and labor use.

The control variables included in X_{dst} (measured at the district level for 1999, 2007 and 2011) are as follows:

(b) Pre-mechanization or initial labor use: Including labor use in 1993 (by gender) allays any concern that gender norms embodied in past labor use determine current labor use and thus act as a confounding factor in our analyses.

(c) Agricultural and demographic characteristics: Crop yields can affect the demand and supply of both farm labor and machinery (e.g. through income effects). Hence we include factors that affect crop yields and which could also be correlated with soil texture - environmental factors (viz. annual temperature and rainfall), proportion of irrigated area, and other soil characteristics (e.g. soil pH, depth and slope).[23]

Additionally, regional demographic characteristics can be correlated with soil endowments and also affect labor demand or supply directly.[24] We, therefore, include the proportion of population belonging to various demographic groups in the district, viz. caste, religion, education and urbanization, as controls.

(d) Landholding size: Existing research suggests that soil quality (Benjamin, 1995), labor use (Rudra and Sen, 1980) and machine uptake (Bhattarai et al., 2016; Wang et al., 2020) can vary systematically with farm size.[25] Inclusion of this variable in X_{dst}, hence, mitigates omitted variable bias concerns in our estimates.

(e) Crop composition: We account for any systematic differences in proportion of area cultivated under different crops since farm labor use by gender can vary by cropping patterns (Bardhan, 1974; Chen, 1989), which in turn can depend on soil characteristics.[26]

(f) Development: Factors that reflect economic growth (e.g. road accessibility and nightlight luminosity) and consequently impact adoption of machinery and labor use in agriculture (Bhattarai et al., 2016) are also controlled for in our analysis. This allays any concern that economic growth determined by agro-ecological soil endowments (Palmer-Jones and Sen, 2003) confounds our causal estimates.

(g) Fertilizer: Lastly, we include fertilizer use per hectare in a district in X_{dst}, since it can vary by soil characteristics and can also directly affect labor use in agriculture (Lamb, 2003; Mahajan and Ramaswami, 2017). [27]

Instrument validity: While the above controls in our empirical specification rule out channels through which soil texture can affect labor use directly, we also test for IV validity explicitly, shown in Table 3. We use data on multiple measures for 1993-94 (prior to mechanization take-off in the late 1990's and beyond) to assess whether they varied systematically by loaminess before the mechanization push that occurred in the country. First, we directly check if male and female labor use in 1993-94 varied by loaminess (Panel A, Table 3). We do not find a significant relationship between loaminess and labor use for either gender before the mechanization take-off.

Next, we test whether loaminess directly impacts the yield of major cereals such as rice and wheat, daily agricultural wage rates (measures of farm productivity) and household incomes (measured by Monthly Per Capita Expenditure (MPCE) as a proxy). Table 3 shows the results for these variables in Panel B and Panel C. Clearly, none of these outcomes vary significantly with loaminess or show a consistent sign in one direction, controlling for state level unobservables and other variables discussed above.

Third, loaminess could directly affect women's labor use if historically women are more disadvantaged in regions with soil texture that require deep tilling, a strength intensive operation. Studies indicate that not only can ploughing requirements differ by crops (Alesina et al., 2013), labor use by gender varies between wheat and rice growing areas in India too (Bardhan, 1974). We, therefore, check if the ratio of area cultivated under wheat and rice in a district systematically differs with loaminess and find no significant relationship (Panel C, Table 3). Nevertheless, recall that we account for crop composition in our empirical specification, as discussed above. Finally, we show later that loaminess only affects uptake of tilling equipment and not of harvesting machines, thus establishing the first stage IV mechanism.

Results

Table 4 reports the first stage estimates for the effect of loaminess on uptake of machines in primary tilling (column (1)), secondary tilling (column (2)) and our measure of mechanization, which sums up primary and secondary tilling (column (3)). The complete set of controls, listed above, are included in these specifications.[28] As expected, we find that there is greater use of mechanized implements for primary and secondary tilling in districts which have a larger proportion of loamy soil relative to clayey soil. These findings are consistent with the process of mechanization discussed in Section 2. Mechanization of primary tilling reduces the marginal cost of mechanizing secondary tilling, since all implements for secondary tillage also draw power from a tractor or a power tiller. Column (3), thus shows a significantly positive effect of loaminess on overall mechanization in Stage 1 tilling.[29] We report Sanderson and Windmeijer (2016) first stage F-Stat for the excluded instrument, which accounts for heteroscedasticity and serial correlation along with district level clustering. The first stage F-Stat, though not very large, is greater than 10 in column (3).[30]

The second stage estimates are reported in Table 5. We include controls sequentially, starting with initial labor use in 1993-94 for the corresponding gender, state and year fixed effects and agricultural and demographic characteristics in column (1). Next, we include average land holding size in a district in column (2) and the proportion of area under different crops in column (3). Development controls are added in column (4) while the last column (5) includes fertilizer use per hectare. An increase in mechanization significantly reduces female labor use (Panel A) as we augment the specification while it has an insignificant effect across all specifications for male labor use (Panel B). Importantly, the Chi-square test of equality of the two coefficients rejects the null hypothesis that the effect of mechanization is same across female and male labor use in all the specifications across columns (1)-(5). This shows that female labor use fell more than male labor due to the shift in production technology towards machines in Stage 1.[31]

Note that as we augment the specification across columns, the negative effect on female labor use is more precisely estimated as the first stage F-Stat becomes larger, thus improving the fit of the model when additional controls are included. Column (5), which includes all controls is, therefore, our preferred specification. An increase in mechanization by one percentage point decreases female labor use per hectare by 2.4% with no impact on male labor use (column (5)). This translates into an elasticity of half, with a 10% increase in mechanization resulting in a 5% fall in women's farm labor use.[32] Overall this elasticity estimate is comparable to that obtained in the literature (Pingali, 2007; Caunedo and Kala, 2021).[33]

Robustness

In this section we conduct multiple robustness checks of the estimates discussed above.

Alternative specifications: We check the robustness of the above results to additional controls and alternative specifications in Table 6. First, given the concerns in Bellemare and Wichman (2020) on interpretation of IHS transformation as a percentage change in the dependent variable, we also present the estimates for the log of the dependent variable in column (1). Here, the number of observations fall to 1066 since some districts report zero female labor use. Second, since our instrument, loaminess, is invariant over time we estimate the local average treatment effect of mechanization on labor use for the entire time period by excluding year fixed effects in column (2). Third, there may be a concern that regions with relatively more loamy soil are also regions with higher population density and hence labor use may vary across these regions. Although controlling for state fixed effects should account for population pressure, which is the highest in the Indo-Gangetic plains, we nevertheless include population density in a district as an additional control in column (3) of Table 6. Finally, the validity of our IV rests on the assumption that the texture of the soil influences only tilling machinery uptake and has no direct effect on labor use, conditional on all controls. Although sowing has not seen a large increase in uptake of mechanized implements, mechanized sowing implements also allow for tilling of soil. We, thus, include sowing machinery in our measure of mechanization in column (4). The results remain robust across all the columns of Table 6.[34]

Weak-instrument: Given that the first stage F-Stat reported in Table 4 is just above 10, a rule of thumb threshold in economics, we test for whether our instrument is weak. First, we present the identification-robust Anderson-Rubin confidence intervals recommended by Andrews et al. (2018), which are efficient regardless of the strength of the instrument (online Appendix Table A.8, columns (1) and (3)). Second, we implement the unbiased IV estimator proposed by Andrews and Armstrong (2017) for an exactly identified model with one endogenous variable. This estimator is based on the reduced form and first-stage regression estimates, under the assumption that the effect of the instrument on the endogenous variable is known (see online Appendix Table A.8, columns (2) and (4))). We continue to find significantly negative effect of mechanization on female labor use but no effect on male labor using both procedures.

Estimate bounds: It is possible that despite the host of observable factors included as controls in our estimation, there remain some confounding factors that affect both labor use and relative loaminess of soil texture.[35] Thus, as an additional robustness exercise we calculate bounds on our 2SLS estimates that take into account plausible direct effects of the IV on the outcome variables using the procedure suggested in Conley et al. (2012) for linear-IV estimation. Details of the methodology and the results are discussed in online Appendix D. Our results are qualitatively unchanged for plausible estimates of any possible direct effects of the IV on labor use (online Appendix Figure D.1).

Discussion

In this section we provide evidence of the mechanism that can explain our main results, as well as the welfare implications of our findings. Our results show that mechanization of tilling operation leads to a significantly greater reduction in women's labor use in Indian agriculture than men's. What explains this gendered effect of the change in production technology? As discussed earlier, mechanization can have gender differentiated impacts on labor use through two channels - direct and indirect. The direct effect of machine uptake in tilling is likely to be greater on male labor since they are relatively more involved in this task. However, to the extent that men primarily operate and maintain tractors in India (Brandtzaeg, 1979), their importance in land preparation could also remain unchanged. On the other hand, deeper tilling can reduce weed growth, hence reduced weeding labor requirement can reduce demand for women's labor. Therefore, we disaggregate our findings above by analyzing the effects of mechanization on labor use in each agricultural operation.

The 2SLS estimates for each operation are reported in Table 7. The findings line up with our claim that since women's and men's labor are imperfect substitutes in agricultural production due to gender-specific specialization in tasks, the adoption of machines in tilling operation displaced women's labor that specializes in the downstream operation of weeding. The Chi-square tests for equality of the coefficient on mechanization for weeding (column (3)) with each operation in Panel A indicate that the decline in female labor in weeding is significantly different from the impact on tilling (p=0.021), sowing (p=0.047) and harvesting (p=0.029). Thus, the overall decline in the usage of women's labor shown in Table 5 is driven by the impact of mechanization on female labor for downstream weeding operation. A one percentage point increase in the intensity of tilling machinery leads to a reduction in women's labor use in weeding by 5.6%, as shown in column (3) of Panel A, Table 7. On the other hand, in Panel B, the coefficient on mechanization for male labor use in weeding is significantly different only from sowing (p=0.099). While the effect of mechanization on male labor in tilling (column 1, Panel B) is negative, it is not significantly different from weeding for men (-1.9% in column (3), Panel B), suggesting an imprecise effect on male labor.[36]

One plausible reason for the insignificant effect on male labor in tilling could be that deep tilling is not performed by hand in Indian agriculture, as discussed earlier using data from the Input Census. Usually, animal operated implements undertake tilling when mechanical power is not used. Thus, mechanization of tilling is more likely to displace animal than human power (Verma, 2006). To test this channel, we estimate the impact of mechanization on usage of animal operated implements utilizing equation 4. The dependent variable now is the area under primary and secondary tilling animal operated implements divided by the total area cultivated in a district in a given year. Indeed, we find a statistically significant reduction in animal operated implements use in tilling by 0.89 percentage points for every one percentage point increase in mechanization.[37]

An alternative mechanism that could explain the estimated fall in female labor use relative to male labor could be a rise in household incomes with increased mechanization. In this scenario women's labor use across *all* agricultural tasks should fall. However, results in Table

7 do not support this hypothesis since we find that the decline in women's labor use is only in the weeding operation. Second, family female labor should fall while hired female labor should substitute for it if only the income effect (for cultivator households) is at play. But estimates for hired and family labor use in Table 8 show that though female family labor declines, it is not compensated by an increase in hired female labor. Instead, female hired labor use falls relative to male hired labor on farms (column (3), p=0.048). The effect of mechanization is insignificant, though negative, on men's family labor use (column (2), Panel B).[38]

Moreover, in line with the existing literature we find positive but not consistently significant increases in all agriculture productivity measures which are likely to accompany rising incomes with mechanization. While wheat and coarse cereal yields increase significantly with mechanization, there is no effect on rice yield and overall cropping intensity.[39] As discussed in Pingali (2007), yield increases are documented only when tilling quality rises substantially due to mechanization. This may not occur always or for all crops.

Lastly, to look at welfare implications of the above findings, we discuss whether women are able to find alternative sources of employment as mechanization reduces their labor use in agriculture. To do this, we estimate the effect of mechanization on women's non-farm employment and find that it does not increase when their labor use in the farm sector sector falls due to mechanization (Panel A, columns (1)-(3), online Appendix Table A.13), a feature consistent with the declining female labor force participation in rural India.[40]

Conclusion

In this paper we analyse the labor impacts of technological change by focusing on the effects of mechanization in agriculture on women's and men's farm labor during 1999-2011 in India. Using the extent of loaminess of the soil, a determinant of the requirement for deep tillage, as an instrument for use of machines for tilling the land, we find that a one percentage point increase in mechanization decreases female labor use per hectare by 2.4%. On the other hand, there is no significant impact on male farm labor usage. This finding is driven by a fall in women's labor in weeding.

Our results extend the broader literature on the effects of technological change on labor. They suggest that in contexts where gendered based division of labor exists, technological change may adversely affect one type of labor relatively more than the other, potentially exacerbating inequities in the labor market. We find that this holds true for women in agriculture. In the Indian context, we also show that women are unable to engage in alternative employment in non-farm sectors, such as manufacturing, construction and services when work opportunities in agriculture decline. Expanding women's labor market opportunities, for example through re-skilling, and/or reducing barriers to their physical mobility may be critical to stemming any decline in women's labor force participation due to mechanization.

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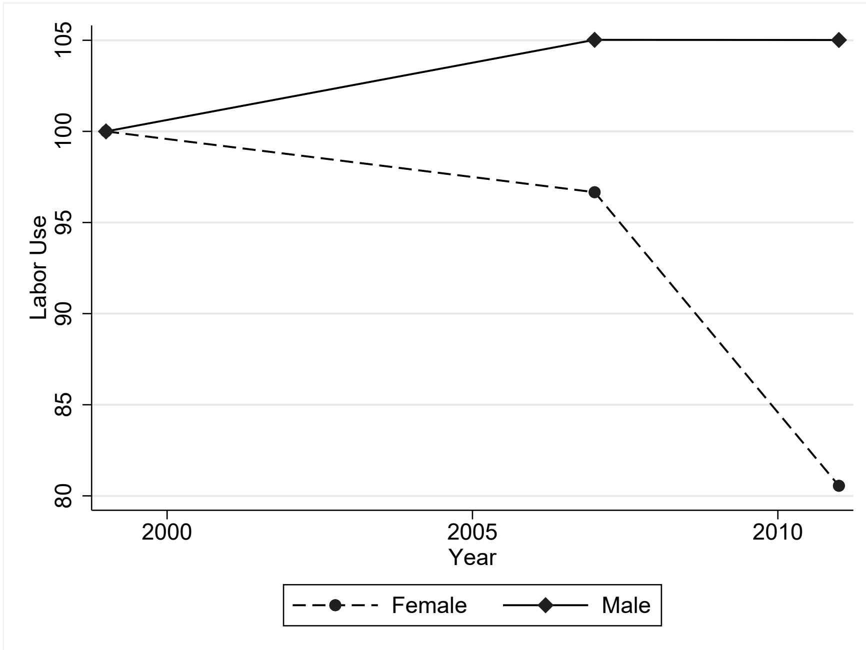
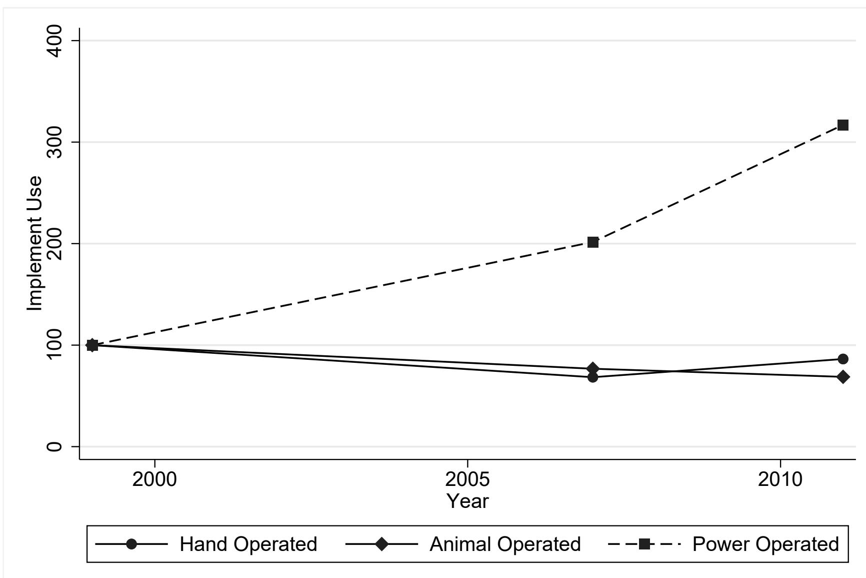


(a) Labor Use (by gender)

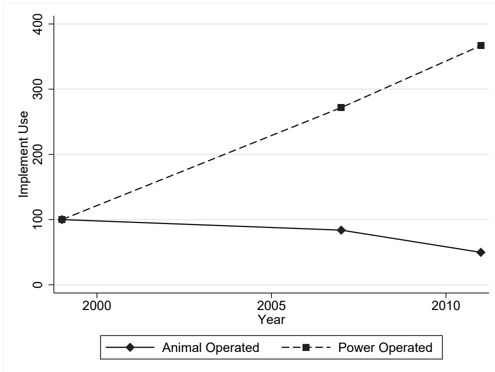


(b) Implement Use (by source of power)

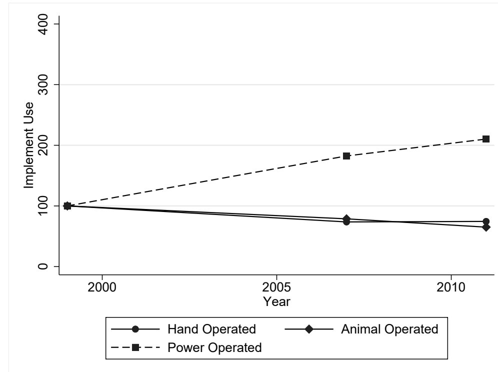
Figure 1: Trends in labor and implement use in Indian agriculture

Source: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds for employment in farm cultivation. Input Survey (1995-97, 2007-08, 2011-12) for farm implements and area cultivated. Authors' own calculations.

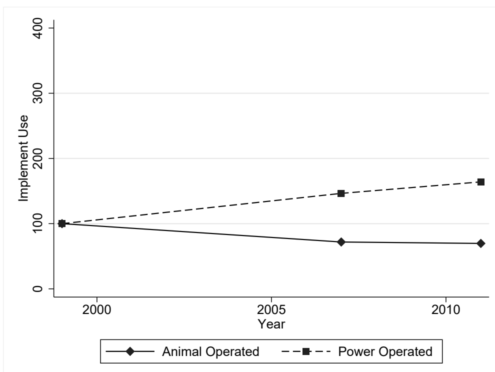
Note: Labor use refers to total number of individuals aged 15-65 working in farm sector in usual status divided by the total area cultivated in a district, by gender. The value of this variable is indexed to 100 in year 1999 and the values in 2007 and 2011 are calculated relative to the value in 1999 for each gender. Implements are grouped by their source of power. The area under all implements for a given power source is aggregated and divided by the total area cultivated in a district. The value of this variables is indexed to 100 in year 1999 and the values in 2007 and 2011 are calculated relative to the value in 1999 for each source of power.



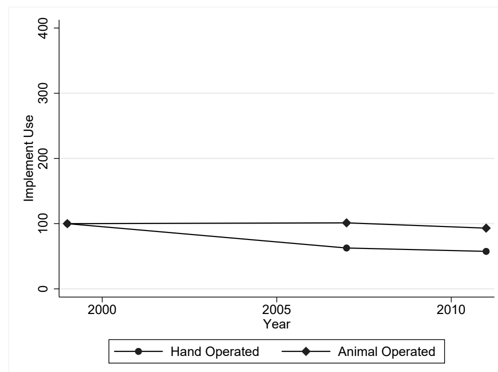
(a) Stage 1: Primary Tilling



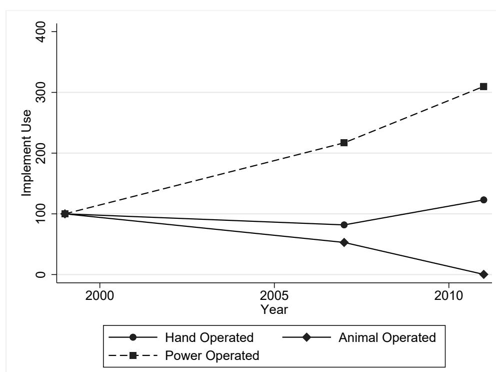
(b) Stage 1: Secondary Tilling



(c) Stage 2: Sowing



(d) Stage 2: Weeding



(e) Stage 3: Harvesting & Threshing

Figure 2: Implement usage: Sources of power by agricultural operations

Source: Input Survey (1995-97, 2007-08, 2011-12) for farm implements and area cultivated. Authors' own calculations.

Note: Implements are grouped by their source of power and the operation for which they are used. The area under all implements in that operation for a given power source is aggregated and divided by the total area cultivated in a district. The value of this variable is indexed to 100 in year 1999 and the values in 2007 and 2011 are calculated relative to the value in 1999 for each power source-operation implement use. The above graphs hence show the growth in usage of implements in different types by operation by their source of power.

Table 1: Gender Division of Labor in Agriculture

Proportion of Females	Tilling	Sowing	Weeding	Harvesting
All Years	0.095	0.328	0.379	0.299
2011	0.104	0.284	0.340	0.265
2007	0.083	0.352	0.390	0.317
1999	0.094	0.369	0.426	0.331

Source: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds. Authors' own calculations.
Note: Each column plots the proportion of females of the total labor used in that operation. All years includes 2011, 2007 and 1999.

Table 2: Summary Statistics: Employment and Mechanization

Variable	1999		2007		2011	
	Mean	SD	Mean	SD	Mean	SD
Total number of females in farm cultivation aged 15-65/cultivated area:						
Female labor per hectare	0.563	0.423	0.544	0.384	0.454	0.350
Total number of males in farm cultivation aged 15-65/cultivated area:						
Male labor per hectare	1.15	.635	1.21	0.674	1.21	0.727
*Area operated under power operated machines*100/cultivated area*						
Mechanization (Primary +Secondary Tilling)	18.6	36.8	40.3	51.9	50.4	62.9
Primary Tilling	7.25	14.3	19.7	25.0	26.6	34.8
Secondary Tilling	11.3	23.9	20.6	28.7	23.8	30.6

Source: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds for employment in farm cultivation. Input Survey (1995-97, 2007-08, 2011-12) for power operated implements and area cultivated. Authors' own calculations. *Note:* A person is classified as working in farm cultivation if either the principal or the subsidiary status of the person includes engagement in farm cultivation either as a family worker/employer or hired laborer. We estimate the total number of workers by gender and divide by area under cultivation to obtain labor use measures. Mechanization is defined as the area under primary and secondary tilling power operated machines divided by the total area cultivated in the district.

Table 3: Agricultural Yields, Wages, Labor Use, Cropping Patterns and Loaminess: Pre-mechanization period

(1)	(2) Loaminess	(3) Observations	(4) R-Squared
Panel A: Labor use			
Female labor per hectare	-.084	385	.62
	(.11)		
Male labor per hectare	.014	385	.77
	(.088)		
Panel B: Wage rate and income			
Wage Rate - Female	-.012	342	.63
	(.043)		
Wage Rate - Male	-.042	371	.72
	(.031)		
MPCE	.018	385	.66
	(.027)		
Panel C: Cropping pattern and yields			
Ratio of cropped area: Wheat by Rice	219	370	.35
	(142)		
Wheat Yield	.025	332	.72
	(.071)		
Rice Yield	-.062	366	.77
	(.062)		

Source: Labor use, daily agricultural wage rate and Monthly Per Capita Expenditure (MPCE) by a household is calculated from National Sample Survey, Employment and Unemployment, 50^{th}round (year 1993). The cropping patterns and yields are taken from ICRISAT-MESO data on Indian districts (year 1993). *Note:* Each row shows the coefficient estimate on loaminess i.e., the difference between loamy and clayey soil shares in a district, when the variable mentioned in Column (1) is regressed on loaminess, state fixed effects, agriculture, demographic, land size, crop composition, development and fertilizer usage. Male and female labor use are defined in the same way as in equation 4 - IHS transformation of the number of individuals aged 15-65 engaged in cultivation per unit cultivated area, after multiplying it by 100. We take log of daily agricultural wage rate, MPCE, wheat and rice yields as the dependent variables. Ratio of cropped area is in levels. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: Effect of Loaminess on Mechanization (First Stage)

	(1)	(2)	(3)
	Primary Tilling	Secondary Tilling	Mechanization Tilling
Loaminess	6.337***	5.540***	11.878***
	(1.903)	(1.760)	(3.335)
Constant	29.864	–34.959	–5.095
	(48.337)	(42.922)	(84.507)
Observations	1077	1077	1077
FS F Stat	11.09	9.90	12.68
Controls			
Initial labor use	✓	✓	✓
State and Year FE	✓	✓	✓
Agriculture-Demographic	✓	✓	✓
Land-size	✓	✓	✓
Crop composition	✓	✓	✓
Development	✓	✓	✓
Fertilizer	✓	✓	✓

Notes: The dependent variable in column (1) is the area operated under primary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. The dependent variable in column (2) is the area operated under secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. Mechanization (Total) in column (3) is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. Loaminess is defined as the difference between loamy and clayey soil shares in a district. All specifications control for initial labor use in agriculture (female), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effect of Mechanization on Farm Labor Use (2SLS)

	(1)	(2)	(3)	(4)	(5)
	Panel A: Female labor per hectare				
Mechanization	–0.034	–0.040*	–0.030**	–0.028**	–0.024**
	(0.024)	(0.024)	(0.014)	(0.014)	(0.011)
Constant	5.098	5.998*	4.444	6.022*	7.420**
	(3.273)	(3.547)	(3.427)	(3.452)	(3.084)
Observations	1077	1077	1077	1077	1077
FS F Stat	3.62	4.55	9.73	9.47	12.68
	Panel B: Male labor per hectare				
Mechanization	0.018	0.006	0.001	0.000	0.001
	(0.013)	(0.008)	(0.004)	(0.004)	(0.003)
Constant	3.819**	5.591***	5.480***	5.558***	5.529***
	(1.677)	(1.130)	(1.260)	(1.263)	(1.137)
Observations	1077	1077	1077	1077	1077
FS F Stat	3.46	4.20	9.49	9.26	12.49
Test of Equality [*p-value*] Female=Male	0.100	0.075	0.034	0.043	0.036
Controls					
Initial labor use	✓	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓	✓
Land-size		✓	✓	✓	✓
Crop composition			✓	✓	✓
Development				✓	✓
Fertilizer input					✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land in a district after multiplying it by 100. Mechanization is defined as the area operated under primary tilling and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. F-Stat varies across Panel A and B since controls for initial labor use and education are gender specific. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Effect of Mechanization on Farm Labor Use (2SLS): Robustness

	(1)	(2)	(3)	(4)
Panel A: Female labor per hectare				
Mechanization	–0.026*	–0.025**	–0.024**	–0.020**
	(0.013)	(0.012)	(0.012)	(0.010)
Constant	1.904	5.688*	7.602**	6.788**
	(3.086)	(3.222)	(3.184)	(3.098)
Observations	1066	1077	1077	1077
FS F Stat	11.66	10.05	11.85	10.95
Panel B: Male labor per hectare				
Mechanization	0.001	0.001	0.002	0.001
	(0.003)	(0.004)	(0.003)	(0.003)
Constant	0.231	5.736***	5.332***	5.553***
	(1.137)	(1.193)	(1.037)	(1.145)
Observations	1077	1077	1077	1077
FS F Stat	12.49	9.04	11.66	10.58
Test of Equality [*p-value*] Female=Male	0.054	0.043	0.036	0.045
Controls				
Initial labor use	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Year FE	✓		✓	✓
Agriculture-Demographic	✓	✓	✓	✓
Land-size	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓
Development	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓
Specification	Log	Year FE dropped	Pop. Density Control	Sowing Mech. included

Notes: In Column (1) the dependent variable is the log of labor use per hectare cultivated land in a district, hence districts where women do not participate in cultivation activities are dropped, resulting in fewer observations. The dependent variable in columns (2)-(4) is an inverse hyperbolic sine transformation of labor use per hectare cultivated land in a district after multiplying it by 100. Mechanization is defined as the area operated under primary tilling and secondary tilling power operated machines divided by the total area cultivated in a district in columns (1)-(3) while it is defined as the area operated under primary tilling, secondary tilling and sowing power operated machines divided by the total area cultivated in a district in column (4), multiplied by 100. All specifications control for initial labor use in agriculture (by gender) and state fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Column (3) additionally controls for population density in a district. F-Stat varies across Panel A and B since controls for initial labor use and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Effect of Mechanization on Farm Labor Use by Agricultural Operation (2SLS)

	(1)	(2)	(3)	(4)	(5)
	Tilling	Sowing	Weeding	Harvesting	Total
	Panel A: Female labor per hectare				
Mechanization	0.004	–0.007	–0.056**	–0.004	–0.021
	(0.011)	(0.015)	(0.024)	(0.016)	(0.015)
Constant	4.874	–0.438	1.524	10.040**	14.583***
	(3.105)	(3.722)	(7.063)	(4.913)	(3.479)
Observations	1077	1077	1077	1077	1077
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.021	0.047	–	0.029	–
	Panel B: Male labor per hectare				
Mechanization	–0.002	0.029*	–0.019	–0.004	0.005
	(0.017)	(0.017)	(0.021)	(0.012)	(0.006)
Constant	8.233*	3.365	3.089	6.824*	6.9698***
	(4.719)	(4.799)	(5.239)	(3.861)	(2.812)
Observations	1077	1077	1077	1077	1077
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.434	0.099	–	0.538	–
Test of Equality [*p-value*] Female=Male	–	–	–	–	0.095
Controls					
Initial labor use	✓	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓	✓
Land-size	✓	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓	✓
Development	✓	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓	✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of total days in a reference week spent by those aged 15-59, in each operation, per hectare cultivated land in a district. The transformation is applied after multiplying labor use by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. F-Stat varies across Panel A and B since controls for initial labor use and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Effect of Mechanization on Farm Labor by Type (2SLS)

	(1)	(2)	(3)
	Overall	Family	Hired
Panel A: Female labor per hectare			
Mechanization	–0.024**	–0.029**	–0.001
	(0.011)	(0.013)	(0.001)
Constant	7.420**	5.119	0.102
	(3.084)	(3.324)	(0.517)
Observations	1077	1077	1077
FS F Stat	12.68	12.68	12.68
Test of Equality [*p-value*] Col.(2)=Col.(3)		0.024	
Panel B: Male labor per hectare			
Mechanization	0.001	–0.004	0.005*
	(0.003)	(0.004)	(0.003)
Constant	5.529***	3.710**	0.573
	(1.137)	(1.621)	(0.639)
Observations	1077	1077	1077
FS F Stat	12.49	12.49	12.49
Test of Equality [*p-value*] Col.(2)=Col.(3)		0.105	
Test of Equality [*p-value*] Female=Male	0.036	0.028	0.048
Controls			
Initial labor use	✓	✓	✓
State and Year FE	✓	✓	✓
Agriculture-Demographic	✓	✓	✓
Land-size	✓	✓	✓
Crop composition	✓	✓	✓
Development	✓	✓	✓
Fertilizer	✓	✓	✓

Notes: The dependent variables in column (1), (2) and (3) are an inverse hyperbolic sine transformation of labor use, family labor use and hired labor use per hectare cultivated land in a district, respectively. The transformation is applied after multiplying the labor use by 100. Labor use is the sum of family and hired labor use. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. F-Stat varies across Panel A and B since controls for initial labor use and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes

[1]Figure A.1 in online Appendix A plots the intensity of usage of tractors and power tillers over time in India using data from the Input Census with the level in 1999 indexed at 100. There was a four-fold increase in tractor usage during this time period.

[2]Around 37% of the working age women were employed in the farm sector in rural India in 1999 and this fell to 25% in 2011. However, their employment in the non-farm sector increased from 7% in 1999 to only 12% in 2011.

[3]For instance, existing evidence shows that uptake of power operated implements in irrigation can increase productivity and hence demand for labor while those in operations such as land preparation, sowing, weeding and harvesting can reduce the demand for labor (Pingali, 2007).

[4]These implements include mould board ploughs, rotavators and cultivators. A majority of the implements used in secondary tillage (disc harrow, cagewheel and leveller) are also tractor or power tiller drawn.

[5]On average, the cost of a tractor is high - approx. 30 times that of an implement used for primary or secondary tilling - in India.

[6]Simply, we can think of men undertaking only tilling while women undertake only weeding. Then in this production function ϵ reflects the degree of substitutability between these two tasks. These tasks are likely to have some degree of substitutability since deeper tilling can reduce the need for weeding.

[7]We do not model consumers' preferences for the agricultural product separately. It is implicit that the price, P, of the final agricultural output is determined optimally in the product market.

[8]See the precise conditions B.32 and B.33 in online Appendix B. Note that all the terms inside the minimum function shown in the proposition are greater than one, hence, the upper bound is strictly greater than one.

[9]While we do not have data on tilling machines prior to 1999, tractor use statistics are available and show that there has been an exponential increase in tractor adoption in India since the 1990s (Singh, 2015; Bhattarai et al., 2016). The number of tractors in India increased from 0.1 million in 1970 to 1 million in 1990 (a rise of 0.9 million in 20 years), to a further 2 million in 2000 (a rise of 1 million in the following decade) and 6 million by 2011 (a rise of 4 million in the next decade) (World Bank Statistics on Agricultural Machinery). A similar increase is documented for power tillers, for which sales increased from 2,220 per year in 1982 to 60,000 per year in 2012 (Bhattarai et al., 2016). This rise can be attributed to farm mechanization policies and programs introduced since 2000 which have offered subsidies on farm equipment purchase and increased farmers' access to credit (Gulati and Juneja, 2020).

[10]Table A.1 shows overall, farm and non-farm employment rates of women and men across the three years

in our analyses. A clear pattern emerges where women's employment rate in the farm sector has declined (36.9% in 1999, 33.3% in 2007 and 25.1% in 2011) while that in the non-farm sector has risen (7.2% in 1999, 8.2% in 2007 and 11.9% in 2011). The decline in women's farm labor, thus, is far more than the increase in the non-farm sector (primarily in the construction sector). Further, women's farm employment has declined for both family and hired labor by a similar magnitude ($\approx$ 8%). At the same time, 55% of women report spending the entire day undertaking domestic household chores in 1999, rising to 61% in 2011.

[11]The number of districts in India increased from 509 in 1999 to 640 in 2011 due to splitting of old districts into two or more. The divided districts were merged into the parent districts to take into account these splits over time.

[12]NSS captures employment at both yearly and weekly level. However, daily employment status only captures workdays in the preceding week of the survey date. This can lead to measurement error since it does not cover the entire agricultural year for an individual. For instance, workers who usually provide farm labor but did not during the survey reference week due to seasonal nature of agricultural work, would not be captured. Thus, we use the yearly employment status as our main measure of farm employment. We also show the robustness of our results to daily employment status as the outcome variable.

[13]These data are available at https://inputsurvey.dacnet.nic.in/.

[14]For instance, for tilling operation the implements are classified as follows - primary tilling equipment consists of plough (wooden, mould board, tractor driven mould board), rotavator, cultivator; secondary tilling equipment consists of hoe (hand, wheel, blade), leveller (hand-held, tractor driven), animal driven wooden plough, disk harrow, tractor driven disc harrow, cagewheel. The details on implement classification for other operations and by source of power are provided in online Appendix C.

[15]The Input Census gives the total area cultivated under a particular agricultural implement in a district. We further classify these implements by stage of operation. Therefore, if a parcel of land undergoes primary tilling using mechanical power operated implements or machines and then undergoes a round of secondary tilling using machines, the mechanization measure will be 200. This is because the same parcel of land can be reported under different machines, therefore, if more than one type of tilling machine is used on a land parcel, the mechanization measure can exceed 100. The data do not allow us to calculate the proportion of land that has been double counted since plot level data are not available. Our measure of mechanization hence should be interpreted as the intensity of mechanization in tilling. Lastly, these data from the Input Census capture use of both owned and hired machinery, without making any distinction between the two. Given that 86% of holdings in India are less than 2 hectares in size, hiring of machines remains an effective alternative for many cultivators. Using Village Dynamics in South Asia (VDSA), a longitudinal survey data collected by ICRISAT from 2009-2014 across 30 villages, we find that 78% farm households use a tractor on

their farm but only 10% of these own one (Afridi et al., 2021). This shows high prevalence of farm machinery hiring in India, similar to other countries (Yang et al., 2013; Mottaleb et al., 2017).

[16]Online Data Appendix C provides a detailed discussion of the NBSS (https://nbsslup.in/) classification system. Note that the NBSS provides data only on the three aggregate soil categories and not for the 13 sub-categories which vary by intensity of silt, clay and loam content.

[17]Online Appendix Table A.2 shows the definition and summary statistics for district level variables used in the analyses. Appendix Table A.3 further provides detailed summary statistics for soil characteristics, while Appendix Table A.4details the socio-demographic characteristics.

[18]Not surprisingly, we find a negative relationship between the two variables, for both men and women, suggesting that labor use is lower in districts where mechanization is higher (Online Appendix Figure A.2).

[19]While there are no districts with zero male labor use, around 11 report zero female labor use. This issue is more acute in operation level analyses, where some districts may report zero labor use for a particular gender in a given operation. The advantage of using the IHS transformation is that it is similar to a logarithm and at the same time accounts for the possibility of zero labor usage in some districts (Burbidge et al., 1988). However, to interpret the IHS regression coefficients as elasticities or percentage changes when the value of the dependent variable before the transformation is small (usually under 10), we follow Bellemare and Wichman (2020) and scale our dependent variable of labor use by multiplying it with 100. This re-scaling ensures that all positive values of the dependent variable before the IHS transformation lie above the threshold of 10.

[20]Note that our estimation strategy requires districts to approximate agricultural labor markets. This assumption has been made in previous studies on Indian rural labor markets (Jayachandran, 2006; Mahajan and Ramaswami, 2017) and is supported by the literature that shows inter-district migration rates for employment are low for India (Munshi and Rosenzweig, 2016; Kone et al., 2018).

[21]Figure A.3 plots the district level fraction of loamy-clayey soil texture, showing significant variation in soil texture within a state across districts.

[22]Detailed definitions of each control variable are in online Appendix Table A.2, A.3, and A.4.

[23]Soil characteristics like pH, depth and slope have been shown to affect plant growth and yield (Islam et al., 1980; Bergstrom et al., 1987; Kapolka and Dollhopf, 2001; Sadras and Calvino, 2001). Irrigation requirements can differ by soil texture (See: MSU Report). Note that it is unlikely that irrigation itself is affected by mechanization in our context. The proportion of irrigated area has remained around 50% for the last few decades - 47% in 1999, 50% in 2007 and 51% in 2011 - in India (Ministry of Agriculture, Land Use Statistics).

[24]Carranza (2014) finds that districts with more loamy soil have a higher percentage of scheduled tribes and a lower percentage of scheduled castes. Caste, religion, education and urbanization have been shown to

affect labor supply by gender in India (Boserup, 1970; Eswaran et al., 2013; Mahajan and Ramaswami, 2017; Afridi et al., 2018).

[25]It is unlikely that farm size has increased in India in response to mechanization. This is because of barriers to land leasing in the country (See: Scroll, Land portal). In fact, landholding size has declined due to land fragmentation from 1.57 hectares in 1999 to 1.4 hectares in 2007 to further 1.23 hectares in 2011.

[26]For instance, studies document greater demand for female labor in rice cultivation due to precision tasks, such as transplanting and weeding (Bardhan, 1974; Mahajan and Ramaswami, 2017) as well as in tea cultivation (Qian, 2008).

[27]Differential nutrient retention across soil texture types requires differential application of fertilizers (See: Soil Types: Advantages and disadvantages).

[28]The reported results are for the female sample with corresponding gender controls for women. The analysis for the male sample gives similar estimates and has been omitted for brevity. However, first stage F-stats are provided for both gender analyses in the 2SLS results that follow.

[29]If loaminess were to affect labor use directly, for instance if household incomes vary systematically with relative loaminess, then we should find a significant increase in take up of machines in *all* operations, including harvesting, in districts with relatively more loamy soil. Table A.5, however, shows an insignificant (imprecise) effect of loaminess on harvesting (sowing) machinery usage. The imprecise but positive effect on sowing is driven by sowing machinery which usually allow for mechanized tilling of soil as well. On the other hand, most harvesters used by Indian farmers are self-propelled and not tractor driven, hence the relative loaminess of the soil clearly does not impact adoption of self-propelled harvesters. These findings again show that our exclusion restriction for 2SLS estimation is valid.

[30]The reported F-Stat is equivalent to that provided in Montiel Olea and Pflueger (2013) for the just identified case. We also show robustness of our estimates to weak instrument concerns later.

[31]The OLS analysis (online Appendix Table A.6) shows that an increase in tilling machine uptake in agriculture is associated with lower male labor use, but there is no effect on female labor. This is expected - since men are more likely to be employed in the rural non-farm sector (discussed above), a decline in the supply of male labor due to increased demand from non-farm sectors would result in higher uptake of mechanization in agriculture. Farm mechanization is thus negatively correlated with the error term for men. The direction of correlation of the female labor error term with mechanization can go in either direction. It will be positive if women are substitutes for men in agriculture when mechanization increases. The correlation will be negative if female labor use falls due to increase in household income through non-farm employment of men.

[32]One percentage point is equal to 5% of mechanization in levels in 1999.

[33]Pingali (2007) provides a summary of studies that assess the impact of mechanization on labor and finds that labor use falls by almost 50% or more across farms that do not use a tractor versus those that do. While there are no estimates available for female labor use in the literature, in a recent paper Caunedo and Kala (2021) examine the effect of providing vouchers for hiring farm machinery. Their intent to treat estimates of offering a voucher on female labor use are around 14% on average, while offering the voucher itself led to an increase in hours of machinery used on the farm by 15%. This implies an elasticity of almost one in their study.

[34]Additionally, if soil texture has *any* correlation with the initial conditions, e.g. if more loaminess is associated with greater soil fertility (a concern ruled out in Table 3) and regions with more fertile soil in the past are also likely to witness divergent economic growth paths Palmer-Jones and Sen (2003) then it would be instructive to check if these differential trends are driving our results. We, thus, account for non-linear time trends in agricultural labor use in a district by interacting initial employment (by gender) with indicator variables for each year as shown in online Appendix Table A.7, columns (1) and (3) for female and male labor, respectively. Further, we control for state specific non-linear trends in columns (2) and (4) of Appendix Table A.7. Our conclusions do not change.

[35]For instance, use of herbicides may also be affected by soil texture, which can directly affect labor use (See: Cornell). While we do not have a perfect measure for herbicides, the Input Census provides data on whether a particular landholding used any pesticide or not. To test the robustness of our results we control for proportion of landholdings that report using pesticide in a district. Our results continue to hold, and are available on request.

[36]The operation level results come with the caveat that they only capture an individual's workdays in the reference week before the survey date. Thus, given that they do not capture the entire agricultural year and that tilling is performed only for short periods at the beginning of a cropping season, there can be error in its measurement leading to imprecise estimates. Table 7, Column (5), also shows the effect of mechanization on total days worked for female labor and male labor in Panel A and B, respectively. It can be seen that while there is a negative effect on female labor use by 2.1%, equal to the estimate using the usual status employment definition in Table 5, it is imprecise. However, the finding that mechanization reduces female labor more than male labor per hectare continues to hold (p=0.082).

[37]The results are reported in online Appendix Table A.9. A direct test would have been to look at use of animals on farm. However, this information is not available in the Input Census.

[38]When we disaggregate our analyses of labor use by family or hired and by gender for each operation, the results support our conclusion that it is the weeding operation that dominates the negative impact on female labor use, for both family and hired female labor (online Appendix Table A.10). These results by task as

well as on hired male labor alleviate any concern that men are more likely to report being employed and that such a reporting error could explain the null effect of mechanization on men. This is because any such reporting error is likely to occur for self-employed than hired labor.

[39]Online Appendix Table A.11, Columns (1)-(3) report the impact of tilling machinery uptake on crop yields for major food grains. The effect on yields is positive, albeit significant only for wheat and coarse cereals. Column (4) shows the effect of uptake of tilling equipment on multiple cropping, defined as gross sown area by net sown area in a district. Again, we see a positive but insignificant effect. Second, if there is increased multiple cropping due to higher timeliness of operations or if crop productivity increases due to mechanization, then the effect on total labor use due to mechanization is ambiguous. In Table A.11, we find that increased machine uptake increases total male labor by 0.8% (column (2)) but total female labor falls by 2.7% (column (1)) for every percentage point increase in mechanization. These findings weaken the possibility that large income effects due to mechanization could alone explain our results in Table 5.

[40]While we find an increase in daily wage rate (reflecting increase in labor productivity) for both men and women due to mechanization, we find suggestive evidence of a larger fall in relative total female earnings due to mechanization (online Appendix Table A.14). This has implications for women's welfare. Details in Appendix A.

AJAE Online Appendix for Gender and Mechanization: Evidence from Indian Agriculture

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Note: The material contained herein is supplementary to the article named in the title and published in the American Journal of Agricultural Economics.

A Additional Results, Figures and Tables

Welfare Implications

A pertinent question is whether there are any implications of the observed impact of mechanization on the gender differences in agricultural wage earnings. Adoption of machinery can reduce labor use but simultaneously increase wage rates through a positive impact on labor productivity, a possibility captured in our theoretical model under certain parametric values. The NSS records wages only for hired farm labor, which may not reflect the overall impact on earnings since family labor constitutes a significant proportion ($\approx 60\%$) of the total farm labor (Appendix Table A.1). Nevertheless, we find an increase in farm daily wage rates for

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both men and women by around 0.6% for a one percentage point increase in mechanization. The rise in wage rates results in a significant increase in male earnings (wage rate multiplied with the number of workdays in a week) by 3.5% but for women there is no significant change. Appendix Table A.14, column (1) reports the impact of mechanization on female (Panel A) and male (Panel B) wage rates while column (2) reports the impact on earnings. The difference in the impact on wage earnings between men and women is insignificant (p=0.16). This provides suggestive evidence that the observed fall in labor use of women may have exacerbated extant gender differences in wage earnings, although the gender difference in our estimates is imprecise.

Are women able to find alternative sources of employment as mechanization reduces their labor use in agriculture? We examine whether non-farm employment in manufacturing, construction and service sectors for women in rural areas is related to agricultural mechanization using our 2SLS specification. Appendix Table A.13 shows no effect of agricultural mechanization on employment in these sectors in rural areas (Columns (1), (2) and (3)) for women in Panel A. We find no evidence for women gaining employment in these sectors. Further, mechanization does not affect employment in any sector in urban areas, suggesting that trends in employment across regions with varying soil texture do not drive our results.

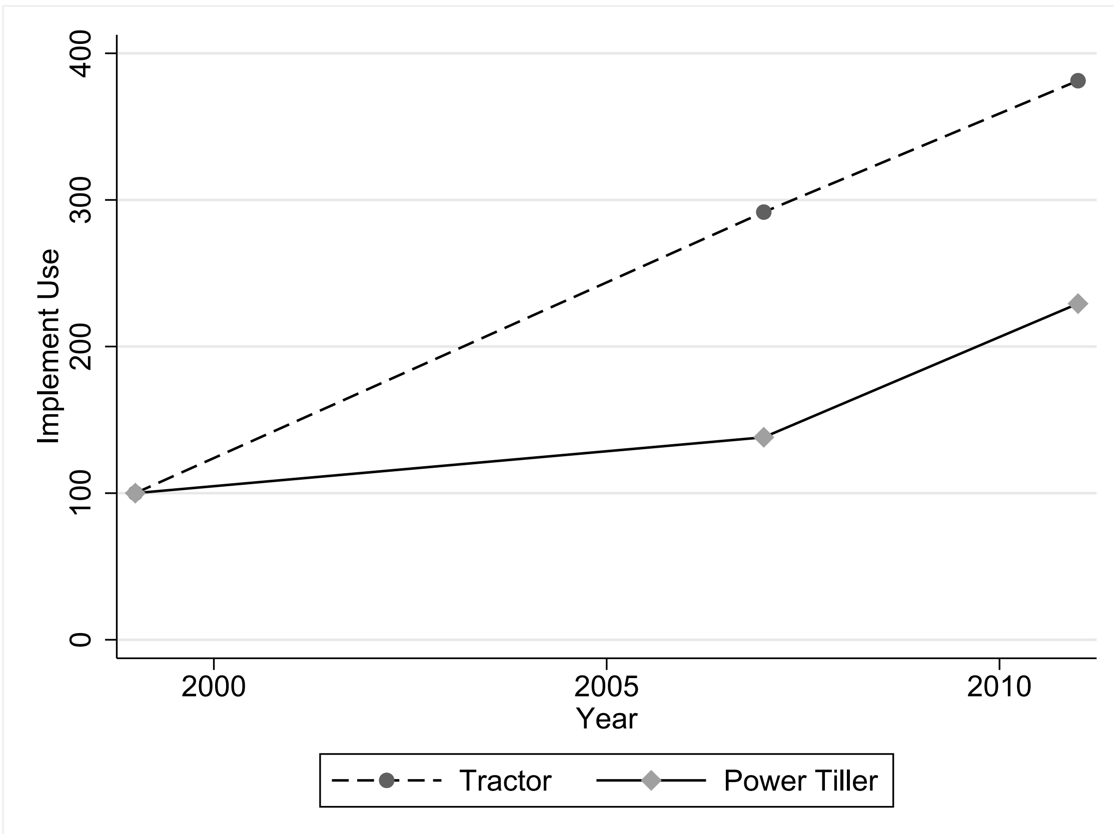
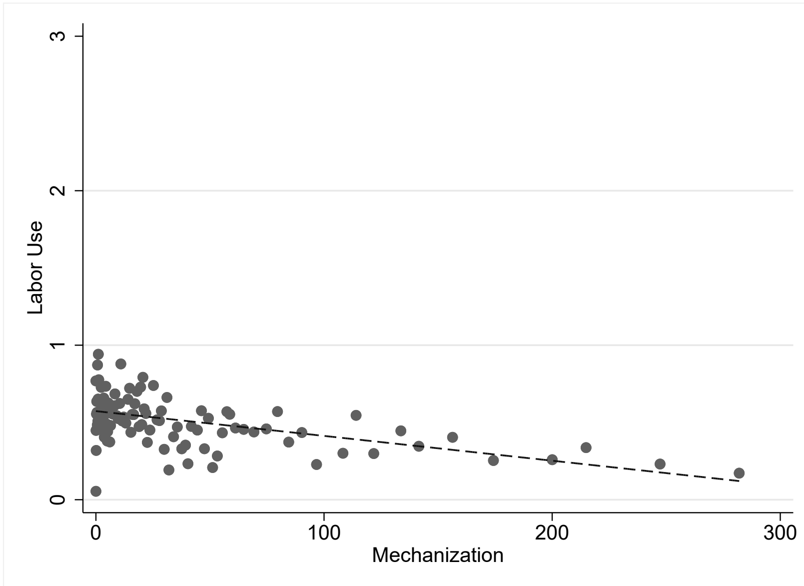
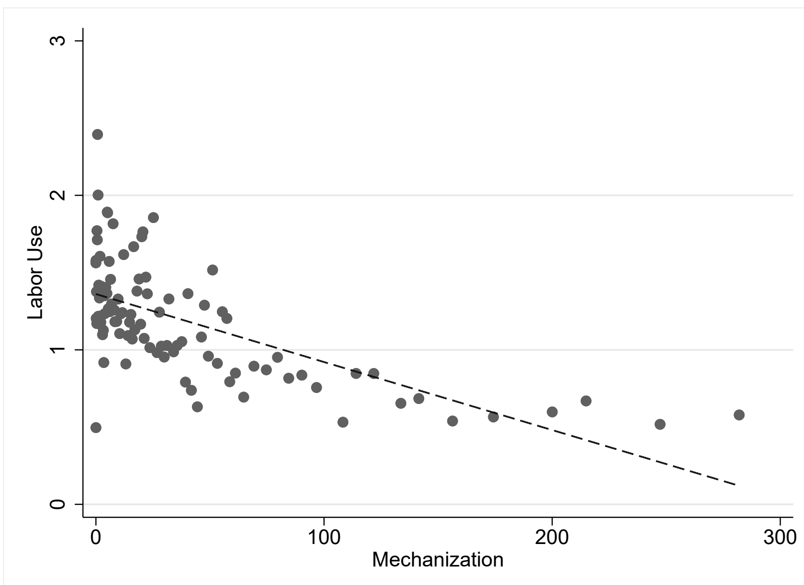


Figure A.1: Tractors and power tillers in Indian agriculture

Source: Input Survey (1995-97, 2007-08, 2011-12). Authors' own calculations.
Note: The area under tractors and power tillers is aggregated and divided by the total area cultivated in a district. The value of this variables is indexed to 100 in year 1999 and the values in 2007 and 2011 are calculated relative to the value in 1999.



(a) Female Labor



(b) Male Labor

Figure A.2: Mechanization and farm labor use

Source: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds for employment in farm cultivation. Input Survey (1995-97, 2007-08, 2011-12) for power operated machines and area cultivated. Authors' own calculations. Authors' own calculations.

Note: Mechanization is defined as the area under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. Labor use refers to total number of individuals aged 15-65 working in farm sector in usual status divided by the total area cultivated in a district, by gender. The line of fit is weighted by district population. District level data has been distributed into 100 bins for visual ease.

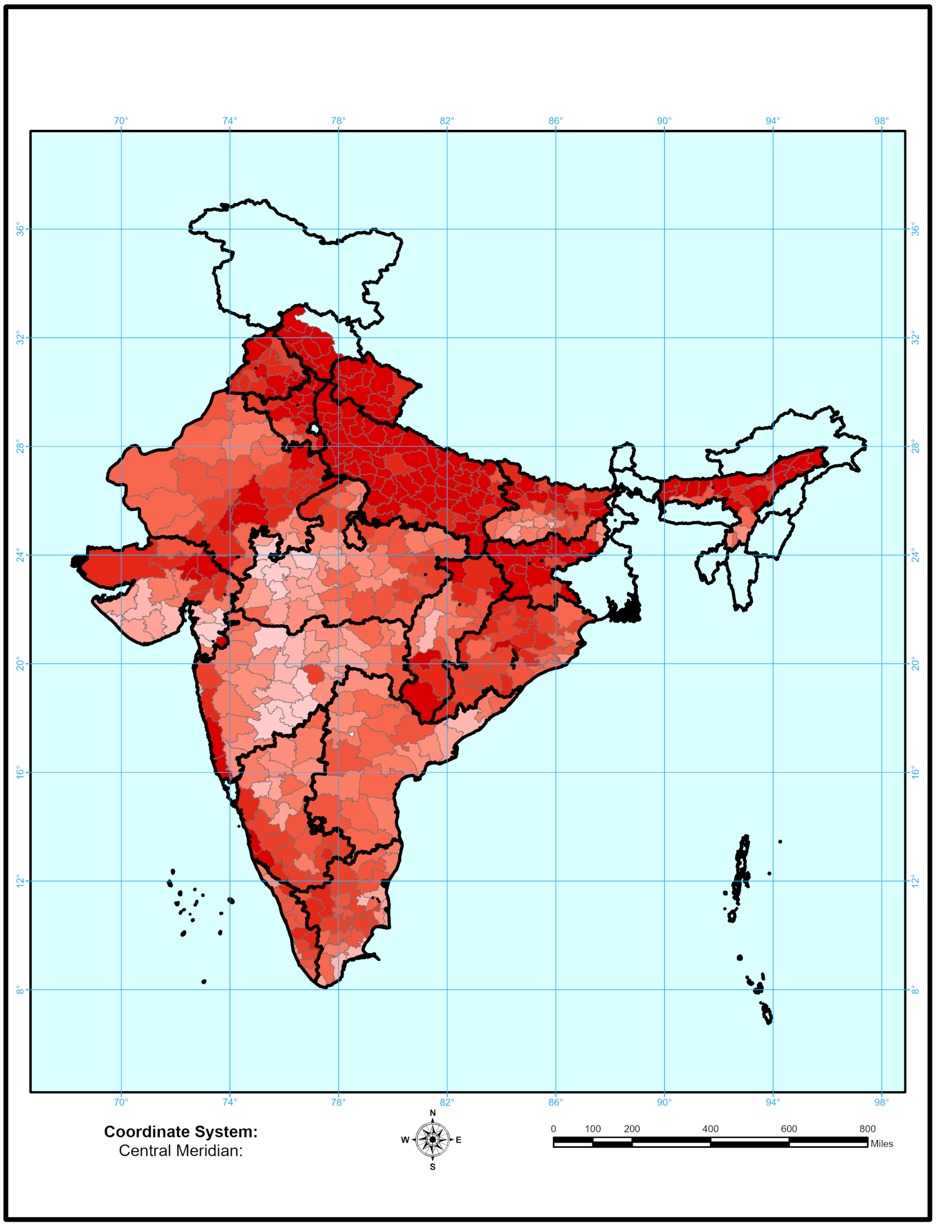


Figure A.3: District level variation in the difference between loamy and clayey soil shares
Source: Digitized by authors from National Bureau of Soil Survey (1995-98) maps.
Note: The districts are clubbed into deciles of difference in loamy and clayey soil shares. Darker shades of red denote higher share of loamy soil as compared to clayey soil. The soil maps for the states of West Bengal, the North-Eastern states of India (Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, Sikkim) and Jammu & Kashmir (now a Union Territory) are unavailable. Some districts of Himachal Pradesh with many missing soil attributes have been dropped from the analysis.

Table A.1: Employment structure in Rural India

	Women 1999	Men 1999	Women 2007	Men 2007	Women 2011	Men 2011
WFPR	0.467	0.859	0.438	0.853	0.366	0.818
Farm	0.369	0.652	0.333	0.607	0.251	0.528
Family farm	0.234	0.461	0.206	0.416	0.158	0.368
Hired farm	0.196	0.292	0.166	0.253	0.109	0.192
Non-farm (all)	0.072	0.286	0.082	0.336	0.119	0.399
Manufacturing	0.037	0.082	0.036	0.083	0.039	0.081
Construction	0.007	0.050	0.015	0.093	0.050	0.159
Services	0.028	0.157	0.031	0.164	0.033	0.167
Non-farm (wage work)	0.029	0.156	0.042	0.199	0.078	0.264
Manufacturing	0.010	0.042	0.010	0.047	0.010	0.047
Construction	0.007	0.042	0.014	0.084	0.050	0.147
Services	0.013	0.072	0.018	0.069	0.019	0.072
Domestic work	0.551	0.004	0.579	0.006	0.613	0.005

Source: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds.

Notes: The table shows the work force participation rates (WFPR) by rural women and men, aged 15-65 across sectors. The employment rates are constructed using the usual status definition of employment. An individual is considered employed in the family farm if she or he is self-employed in farming activity either in the principal or the subsidiary status. An individual is considered employed as hired farm laborer if she or he worked as a casual farm laborer for wage either in the principal or the subsidiary status. It is possible that an individual is classified both in family farm and as hired laborer. This happens when one of these is a principal activity while the other is a subsidiary activity. See Appendix Section C for more details. Similarly, an individual is considered employed in manufacturing sector if she or he was self-employed or worked as a laborer for wage in this sector either in the principal or the subsidiary status. The other definitions follow in the similar way. If an individual was only engaged in household domestic chores during the major work day in the principal status then that individual is classified as a domestic worker. Domestic chores undertaken by individuals outside the work day of 8 hours are not captured by the NSS data.

Table A.2: Summary Statistics: Control Variables

Variable	Definition	Mean	SD
Initial Employment (1993-94) (Number aged 15-65):			
Female Labor	Total females in farm cultivation/cultivated area	0.682	0.716
Male Labor	Total males in farm cultivation/cultivated area	1.46	1.34
Agriculture:			
Soil	Soil Ph, Depth, Slope (See Table A.3)		
Rainfall	Total yearly precipitation (mm)	1204	684
Temperature	Mean yearly temperature (^oC)	25.6	1.55
Irrigated Area	Proportion of sown area under irrigation	0.497	0.289
Demographic:			
Urban population	Proportion of urban population	0.235	0.154
Others	Caste, Religion and Education (See Table A.4)		
Other Agriculture:			
Land-size	Average size of landholding (ha)	1.38	1.15
Crop Composition (Proportion of Gross Sown Area (GSA)):			
Wheat	Area under wheat/GSA	0.167	0.184
Rice	Area under rice/GSA	0.336	0.284
Coarse cereals	Area under coarse cereals/GSA	0.134	0.158
Pulses	Area under pulse/GSA	0.103	0.103
Oil seeds	Area under oil seeds/GSA	0.105	0.134
Horticulture	Area under fruits & vegetables/GSA	0.030	0.053
Other	Area under other crops/GSA	0.126	0.163
Development:			
Approach road	Proportion of villages with paved approach road	0.83	0.175
Night lights	Annual relative night-time luminosity (0-63)	4.86	3.86
Fertilizer Input:			
Fertilizers:			
Nitrogenous	Fertilizer consumption (kg/’000 ha)	0.093	0.071
Phosphorous	Fertilizer consumption (kg/’000 ha)	0.032	0.024
Potash	Fertilizer consumption (kg/’000 ha)	0.014	0.018

Source: Labor Supply, Demographics (National Sample Survey, Employment and Unemployment rounds: 50^{th}, 55^{th}, 64^{th}, 68^{th}); Implements, Average landholding, Rainfall and Temperature (IMD), Crop composition (District-wise Crop Production Statistics, Ministry Of Agriculture); Irrigated area (Land Use Statistics of India, Ministry of Agriculture); Urban, Road access (Census of India: 2001, 2011); Nightlights (DMSP); Fertilizer (CMIE (Fertilizer Association of India)).
Note: Average value across districts across the three years are shown for brevity.

Table A.3: Variable Definition and Summary Statistics: Soil Characteristics

Variable	Definition	Mean	SD
Soil Depth:			
Extremely Shallow	Proportion of soil with depth <10cm	0.011	0.036
Very Shallow	Proportion of soil with depth 10-25cm	0.053	0.106
Shallow	Proportion of soil with depth 25-50cm	0.066	0.111
Slightly Deep	Proportion of soil with depth 50-75cm	0.076	0.121
Moderately Deep	Proportion of soil with depth 75-100cm	0.075	0.114
Deep	Proportion of soil with depth 100-150cm	0.621	0.349
Very Deep	Proportion of soil with depth >150cm	0.098	0.19
Soil Slope:			
Level	Proportion of soil with gradient 0-1%	0.237	0.261
Very gentle	Proportion of soil with gradient 1-3%	0.403	0.224
Gentle	Proportion of soil with gradient 3-8%	0.233	0.232
Moderate	Proportion of soil with gradient 8-15%	0.065	0.099
Moderate steep	Proportion of soil with gradient 15-30%	0.045	0.096
Steep	Proportion of soil with gradient 30-50%	0.017	0.056
Soil pH:			
Strongly Acidic	Proportion of soil with pH <4.5	0.003	0.018
Moderately Acidic	Proportion of soil with pH 4.5-5.5	0.056	0.168
Slightly Acidic	Proportion of soil with pH 5.5-6.5	0.194	0.24
Neutral	Proportion of soil with pH 6.5-7.5	0.255	0.219
Slightly Alkaline	Proportion of soil with pH 7.5-8.5	0.391	0.272
Moderately Alkaline	Proportion of soil with pH 8.5-9.5	0.088	0.142
Strongly Alkaline	Proportion of soil with pH >9.5	0.013	0.048
Soil Surface Texture:			
Sandy	Proportion of soil with sandy texture	0.094	0.165
Loamy	Proportion of soil with loamy texture	0.631	0.278
Clayey	Proportion of soil with clayey texture	0.274	0.276

Source: National Bureau of Soil Survey (1995-98).
Note: Average value across districts are shown.

Table A.4: Variable Definition and Summary Statistics: Demographic Controls

Variable	Definition	Mean	SD
Demographic:			
Caste (Proportion)			
ST	Scheduled Tribes population	0.102	0.173
SC	Scheduled Castes population	0.21	0.117
OBC	Other Backward Castes population	0.427	0.218
Others	Other castes population	0.261	0.199
Religion (Proportion)			
Hindu	Hindu population	0.852	0.176
Muslim	Muslim population	0.104	0.137
Christian	Christian population	0.017	0.055
Others	Other religions population	0.028	0.115
Female Education (Proportion age 15-65)			
Illiterate	Females who are illiterate	0.534	0.193
Up to Secondary	Females educated up to secondary school level	0.410	0.165
Higher Secondary & above	Females educated up to higher secondary level & above	0.056	0.052
Male Education (Proportion age 15-65)			
Illiterate	Males who are illiterate	0.286	0.141
Up to Secondary	Males educated up to secondary school level	0.594	0.121
Higher Secondary & above	Males educated up to higher secondary level & above	0.120	0.066

Source: Demographics: National Sample Survey's 55^{th}, 64^{th}, 68^{th} rounds.
Note: Average value across the three years shown for brevity.

Table A.5: Effect of Loaminess on Usage of Other Power Operated Implements

	(1)	(2)
	POI Sowing	*POI Harvesting*
Loaminess	2.134*	–0.394
	(1.258)	(1.797)
Constant	–21.277	20.129
	(27.572)	(43.153)
Controls		
Initial labor use	✓	✓
State and Year FE	✓	✓
Agriculture-Demographic	✓	✓
Land-size	✓	✓
Crop composition	✓	✓
Development	✓	✓
Fertilizer	✓	✓

Notes: The dependent variable in column (1) is the area operated under sowing power operated machines divided by the total area cultivated in a district, multiplied by 100. The dependent variable in column (2) is the area operated under harvesting and threshing power operated machines divided by the total area cultivated in a district, multiplied by 100. Loaminess is defined as the difference between loamy and clayey soil shares in a district. The controls refer to the second stage controls for female labor use in the second stage equation. All specifications control for initial labor use in agriculture (female), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6: Effect of Mechanization on Farm Labor Use (OLS)

	(1)	(2)
	Female labor per hectare	*Male labor per hectare*
Mechanization	0.000	–0.001***
	(0.001)	(0.000)
Constant	6.918***	5.540***
	(2.080)	(1.200)
Observations	1077	1077
R-Squared	0.52	0.77
Controls		
Initial labor use	✓	✓
State and Year FE	✓	✓
Agriculture-Demographic	✓	✓
Land-size	✓	✓
Crop composition	✓	✓
Development	✓	✓
Fertilizer	✓	✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of total labor (total number of females (column 1) and males (column 2) in farm cultivation aged 15-65) in a district after multiplying it by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for total initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Effect of Mechanization on Farm Labor Use (2SLS) - Additional Robustness

	(1)	(2)	(3)	(4)
	Female labor per hectare		*Male labor per hectare*	
Mechanization	–0.023**	–0.021**	0.001	0.002
	(0.011)	(0.010)	(0.003)	(0.003)
Constant	7.228**	6.290**	5.557***	5.842***
	(3.024)	(2.685)	(1.127)	(1.128)
Observations	1077	1077	1077	1077
FS F Stat	13.02	14.91	13.05	15.36
Controls				
Initial labor use	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓
Land size	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓
Development	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓
Additional Controls				
Initial District Employment × Time	✓	✓	✓	✓
State × Time		✓		✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land in a district after multiplying it by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Here *Time* is defined as indicator variables for each year. Regressions weighted by district population. F-Stat varies across female and male columns since controls for initial labor use and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.8: Effect of Mechanization on Farm Labor Use (2SLS) - Weak IV Robust Estimators

	(1) Anderson-Rubin	(2) Andrews Est.	(3) Anderson-Rubin	(4) Andrews Est.
	Female labor per hectare		*Male labor per hectare*	
Mechanization	–0.024**	–0.022**	0.001	0.000
95% CI	[-0.062, -0.005]	[-0.042, -0.001]	[-0.006, 0.01]	[-0.004, 0.006]
Observations	1077	1077	1077	1077
Controls				
Initial labor use	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓
Land size	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓
Development	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land in a district after multiplying it by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refer to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses in columns (1) and (3) for the Anderson-Rubin estimator given in Andrews et al. (2018), while columns (2) and (4) do not cluster the standard errors based on the Andrews and Armstrong (2017) method. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Effect of Mechanization on Animal Operated Implements (2SLS)

	(1)	(2)	(3)
	AOI *Primary Tilling*	*AOI* *Secondary Tilling*	*AOI* *Primary & Secondary Tilling*
Mechanization	–0.198	–0.696**	–0.895**
	(0.176)	(0.340)	(0.431)
Constant	84.347	196.523**	280.870***
	(53.763)	(82.477)	(104.042)
Observations	1077	1077	1077
FS F Stat	12.49	12.49	12.49
Controls			
Initial labor use	✓	✓	✓
State and Year FE	✓	✓	✓
Agriculture-Demographic	✓	✓	✓
Land-size	✓	✓	✓
Crop composition	✓	✓	✓
Development	✓	✓	✓
Fertilizer	✓	✓	✓

Notes: The dependent variable in column (1) is the area under animal operated implements in primary tilling operation divided by the total area cultivated in a district, multiplied by 100. The dependent variable in column (2) is the area under animal operated implements in secondary tilling operation divided by the total area cultivated in a district, multiplied by 100. The dependent variable in column (3) is the area under animal operated implements in primary and secondary tilling operation divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (male), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (male). Land size refers to landholding size while crops refer to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Effect of Mechanization on Farm Labor Use by Agricultural Operation (2SLS)

	(1)	(2)	(3)	(4)
	Tilling	Sowing	Weeding	Harvesting
Panel A: Female labor per hectare				
Family Labor	0.002	–0.011	–0.046**	0.000
	(0.009)	(0.015)	(0.021)	(0.016)
Constant	1.865	3.053	2.544	7.541*
	(2.874)	(3.663)	(6.581)	(4.372)
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.039	0.111	.	0.052
Hired Labor	0.002	0.015	–0.037**	0.008
	(0.007)	(0.013)	(0.019)	(0.015)
Constant	7.569***	–5.401	–0.101	7.051
	(2.387)	(3.608)	(5.406)	(4.574)
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.054	0.027	.	0.044
Panel B: Male labor per hectare				
Family Labor	–0.008	0.031*	–0.019	–0.001
	(0.016)	(0.018)	(0.020)	(0.013)
Constant	6.492*	5.333	3.601	4.879
	(3.700)	(5.385)	(5.130)	(4.560)
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.626	0.085	.	0.449
Hired Labor	0.029*	0.033*	–0.009	0.011
	(0.018)	(0.017)	(0.016)	(0.014)
Constant	3.703	–5.240	1.051	10.711**
	(5.897)	(4.416)	(4.595)	(4.321)
Test of Equality [*p-value*] Col(3)=Col(1)/(2)/(4)	0.093	0.072	.	0.340
Controls				
Initial labor use	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓
Land size	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓
Development	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓

Notes: The table reports the coefficients on the effect of mechanization on labor use by family and hired labor across agricultural operations. The dependent variable is an inverse hyperbolic sine transformation of total days in a reference week spent by those aged 15-59, in each operation, per hectare cultivated land in a district. The transformation is applied after multiplying the labor use by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. First stage F-Stat is 12.94 for female labor and 12.95 for male labor usage (different since controls for initial labor use and education are gender specific.). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: Effect of Mechanization on Yield and Cropping Intensity (2SLS)

	(1)	(2)	(3)	(4)
	Yield			*Cropping*
	Rice	Wheat	Coarse Cereals	*Intensity*
Mechanization	0.002	0.008**	0.007*	0.029
	(0.004)	(0.004)	(0.004)	(0.268)
Constant	0.287	7.469*	1.912	99.545**
	(0.883)	(4.157)	(2.131)	(49.390)
Observations	982	806	959	1077
FS F Stat	11.21	5.07	12.32	14.20
Controls				
Initial Y	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓
Land size	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓
Development	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓

Notes: The dependent variable in columns (1)-(3) is the log of yield of the given crop in a district. Cropping Intensity is defined as Gross Cropped Area divided by Net Sown Area in a district. All specifications control for initial values of the dependent variable (initial Y), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.12: Effect of Mechanization on Total Farm Labor (2SLS)

	(1)	(2)
	Total Female Labor	*Total Male Labor*
Mechanization	–0.027*	0.008*
	(0.016)	(0.004)
Constant	15.513***	13.051***
	(4.311)	(1.237)
Observations	1077	1077
FS F Stat	13.97	13.35
Test of Equality [*p-value*] Female=Male	0.03	
Controls		
Initial labor use	✓	✓
State and Year FE	✓	✓
Agriculture-Demographic	✓	✓
Land-size	✓	✓
Crop composition	✓	✓
Development	✓	✓
Fertilizer	✓	✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of total labor (total number of females (column 1) and males (column 2) in farm cultivation aged 15-65) in a district. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for total initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. F-Stat varies across female and male columns since controls for initial labor use and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.13: Effect of Mechanization on Non-Agricultural Labor (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Female labor					
	Rural			*Urban*		
	Manu	Cons	Serv	Manu	Cons	Serv
Mechanization	–0.009	0.015	0.015	–0.005	–0.005	–0.003
	(0.012)	(0.010)	(0.010)	(0.014)	(0.012)	(0.012)
Constant	5.933	–6.446**	3.051	–0.101	–7.370**	–0.305
	(4.263)	(2.879)	(2.035)	(3.795)	(3.554)	(2.798)
Observations	1077	1077	1077	1077	1077	1077
FS F Stat	13.06	13.06	13.06	13.06	13.06	13.06
	Panel B: Male labor					
Mechanization	–0.009	0.022**	–0.002	–0.003	0.007	0.000
	(0.009)	(0.010)	(0.004)	(0.007)	(0.009)	(0.003)
Constant	3.755*	–1.712	3.443***	3.128*	–0.639	5.289***
	(1.993)	(2.905)	(1.042)	(1.777)	(2.251)	(0.746)
Observations	1077	1077	1077	1050	1050	1050
FS F Stat	12.49	12.49	12.49	12.83	12.83	12.83
Controls						
Initial labor use	✓	✓	✓	✓	✓	✓
State and Year FE	✓	✓	✓	✓	✓	✓
Agriculture-Demographic	✓	✓	✓	✓	✓	✓
Land-size	✓	✓	✓	✓	✓	✓
Crop composition	✓	✓	✓	✓	✓	✓
Development	✓	✓	✓	✓	✓	✓
Fertilizer	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is an inverse hyperbolic sine transformation of proportion of female (panel A) and male (panel B) aged 15-65 working in manufacturing (columns 1 and 4), construction (columns 2 and 5) and services (columns 3 and 6) in a district. The transformation is applied after multiplying the proportion by 100. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. F-Stat varies across Panel A and B since controls for initial labor use and education are gender specific. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.14: Effect of Mechanization on Wage Rate and Earnings (2SLS)

	(1)	(2)
	Wage Rate	*Wage Earnings*
Panel A: Females		
Mechanization	0.007*	0.014
	(0.004)	(0.011)
Observations	806	806
FS F Stat	7.59	5.93
Panel B: Males		
Mechanization	0.006*	0.037**
	(0.003)	(0.016)
Observations	971	971
FS F Stat	9.87	9.85
Test of Equality [*p-value*] Female=Male	0.628	0.160
Controls		
Initial Y	✓	✓
State and Year FE	✓	✓
Agriculture-Demographic	✓	✓
Land-size	✓	✓
Crop composition	✓	✓
Development	✓	✓
Fertilizer	✓	✓

Notes: The dependent variable in column (1) is the log of average daily wage paid for casual labor in cultivation in a district. The dependent variable in column (2) is the log of average weekly earnings (wage per day multiplied with number of days worked in a week) from casual-hired labor in cultivation in a district. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district, multiplied by 100. The number of observations fall because wage data is available only for the district-years where hired labor use is reported. All specifications control for initial wage rate and earnings in agriculture (by gender) in column (1) and (2) respectively, state fixed effects and year fixed effects. Agriculture and demographic controls include depth, pH and slope of the soil, irrigation, climate, fraction of urban population, caste, religion, education (by gender). Land size refers to landholding size while crop composition refers to proportion of area under different crops. Development controls include access to roads and night light luminosity. Fertilizer controls for per hectare use of nitrogen, phosphorus and potash in a district. Regressions weighted by district population. F-Stat varies across Panel A and B since controls for initial wage rate/earnings and education are gender specific. Robust standard errors clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Theoretical model

Given the theoretical framework described in Section 3, we derive the following proposition:

Proposition B.1 *Under the competitive equilibrium,*

(a) The female-land labor intensity $\left(\frac{F}{T}\right)$ *decreases when* A_a *increases, i.e.* $\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0$ *when the following condition holds:*

$$\epsilon \in \left(0, \min\left[\frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha}\cdot\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right]\right),$$

where both the terms appearing in the min *function are strictly greater than 1 along with* $Q = \left(\frac{\theta}{1-\theta}\right)^{\left(\frac{\sigma}{1-\sigma}\right)}\left(\frac{w_m A_K}{rA_L}\right) > 1$.

(b) The male-land labor intensity $\left(\frac{M}{T}\right)$ *decreases when* A_a *increases, i.e.* $\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} < 0$ *when the following condition holds:*

$$\epsilon > \frac{\log(Q)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)} \quad \textit{where} \quad \frac{\log(Q)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)} < 1.$$

(c) The male-female labor intensity $\left(\frac{M}{F}\right)$ *increases when* A_a *increases, i.e.* $\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0$ *when the following condition holds:*

$$\epsilon \in \left(0, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right) \quad \textit{where} \quad \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]} > 1.$$

All three results, namely (a) - (c) above, jointly hold for a set of ϵ *that has a lower bound less than or equal to one (but not zero) and the upper bound strictly greater than one but finite (precisely the conditions B.27 and B.28 derived below).*

Proof of proposition:

Partially differentiating the composite labor expression (equation 2) with respect to F and M gives us,

$$\frac{\partial L}{\partial F} = \alpha(F)^{\left(\frac{-1}{\epsilon}\right)}[\alpha(F)^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha)(M)^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{1}{(\epsilon-1)}},$$

$$\frac{\partial L}{\partial M} = (1-\alpha)(M)^{\left(\frac{-1}{\epsilon}\right)}[\alpha(F)^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha)(M)^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{1}{(\epsilon-1)}}$$

respectively. Since the marginal products of the factor inputs can be expressed as

$$\frac{\partial Y}{\partial F} = \frac{\partial Y}{\partial L}\frac{\partial L}{\partial F}, \quad \textit{and,} \quad \frac{\partial Y}{\partial M} = \frac{\partial Y}{\partial L}\frac{\partial L}{\partial M},$$

taking the ratio of the value of marginal product of male labor to that of the female labor we get,

$$\frac{w_m}{w_f} = \frac{\frac{\partial L}{\partial M}}{\frac{\partial L}{\partial F}},$$

which ensures that

$$\frac{M}{F} = \left[\frac{1-\alpha}{\alpha}\frac{w_f}{w_m}\right]^{\epsilon}.$$

Now, using this above relationship and equation (2), it is straightforward to show that

$$L = F\frac{1}{\alpha^{\epsilon}(w_m)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}} = M\frac{1}{(1-\alpha)^{\epsilon}(w_f)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}}$$

where $\Delta \equiv [\alpha^{\epsilon}(w_m)^{(\epsilon-1)} + (1-\alpha)^{\epsilon}(w_f)^{(\epsilon-1)}]$. Further for notational simplicity, we denote $\Omega \equiv \frac{1}{(1-\alpha)^{\epsilon}(w_f)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}}$, $\delta \equiv \frac{1}{\alpha^{\epsilon}(w_m)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}}$ and $\Theta \equiv [\theta(A_L L)^{\frac{(\sigma-1)}{\sigma}} + (1-\theta)(A_K T)^{\frac{(\sigma-1)}{\sigma}}]$ so that we can write $L = F\delta = M\Omega$ and $Y = A_a\left[\Theta\right]^{\frac{\sigma}{(\sigma-1)}}$.
It can be verified that differentiating the final output Y with respect to M and T and some simplifications thereafter can give us

$$\frac{\partial Y}{\partial M} = A_a(\theta)A_L^{'}\left[\theta + (1-\theta)\left(\frac{A_K T}{A_L^{'}M}\right)^{\frac{(\sigma-1)}{\sigma}}\right]^{\frac{1}{(\sigma-1)}},$$

$$\frac{\partial Y}{\partial T} = A_a(1-\theta)A_K\left[(1-\theta) + \theta\left(\frac{A_L^{'}M}{A_K T}\right)^{\frac{(\sigma-1)}{\sigma}}\right]^{\frac{1}{(\sigma-1)}}$$

respectively, where $A_L^{'} \equiv A_L\Omega$. Now, using this expression in the equilibrium condition for male labor, we derive the following equilibrium male labor use

$$M = \frac{A_K T}{A_L^{'}}\left[\frac{1}{1-\theta}\left[\frac{PA_a(\theta)A_L^{'}}{w_m}\right]^{(1-\sigma)} - \frac{\theta}{1-\theta}\right]^{\frac{\sigma}{1-\sigma}}.$$

Since, M cannot be negative, the following condition must be satisfied

$$\left[\frac{1}{1-\theta}\left[\frac{PA_a(\theta)A_L^{'}}{w_m}\right]^{(1-\sigma)} - \frac{\theta}{1-\theta}\right] \equiv \odot \geq 0.$$

If we repeat the exercise for women's labor use, we arrive at the following:

$$F = \frac{A_K T}{A_L^{''}}\left[\frac{1}{1-\theta}\left[\frac{PA_a(\theta)A_L^{''}}{w_f}\right]^{(1-\sigma)} - \frac{\theta}{1-\theta}\right]^{\frac{\sigma}{1-\sigma}}$$

where $A_L^{''} \equiv A_L\delta$. Similarly, to guarantee positive labor use for women, we need the following restriction

$$\left[\frac{1}{1-\theta}\left[\frac{PA_a(\theta)A_L^{''}}{w_f}\right]^{(1-\sigma)} - \frac{\theta}{1-\theta}\right] \equiv \otimes \geq 0.$$

Repeating the exercise for the factor land gives us the following

$$T = \frac{A_L^{'}M}{A_K}\left[\frac{1}{\theta}\left[\frac{PA_a(1-\theta)A_K}{r}\right]^{(1-\sigma)} - \frac{1-\theta}{\theta}\right]^{\frac{\sigma}{1-\sigma}}$$

which can also be expressed in terms of F as follows,

$$T = \frac{A_L^{''}F}{A_K}\left[\frac{1}{\theta}\left[\frac{PA_a(1-\theta)A_K}{r}\right]^{(1-\sigma)} - \frac{1-\theta}{\theta}\right]^{\frac{\sigma}{1-\sigma}}.$$

To guarantee a positive amount of land, we need the condition

$$\left[\frac{1}{\theta}\left[\frac{PA_a(1-\theta)A_K}{r}\right]^{(1-\sigma)} - \frac{1-\theta}{\theta}\right] \equiv \tau \geq 0.$$

It can be verified that

(B.1)
$$\frac{\partial \odot}{\partial A_a} = \left[\frac{1}{1-\theta}\left[\frac{P(\theta)A_L'}{w_m}\right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma}\right],$$

(B.2)
$$\frac{\partial \otimes}{\partial A_a} = \left[\frac{1}{1-\theta}\left[\frac{P(\theta)A_L''}{w_f}\right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma}\right],$$

and finally,

(B.3)
$$\frac{\partial \tau}{\partial A_a} = \left[\frac{1}{\theta}\left[\frac{P(1-\theta)A_K}{r}\right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma}\right].$$

Differentiating the optimal demand for male and female labor M and F w.r.t. A_a we get,

(B.4)
$$\frac{\partial M}{\partial A_a} = \frac{A_K}{A_L'}\frac{\partial T}{\partial A_a}[\odot]^{\frac{\sigma}{1-\sigma}} + \frac{A_K T}{A_L'}\left(\frac{\sigma}{1-\sigma}\right)[\odot]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial \odot}{\partial A_a},$$

(B.5)
$$\frac{\partial F}{\partial A_a} = \frac{A_K}{A_L''}\frac{\partial T}{\partial A_a}[\otimes]^{\frac{\sigma}{1-\sigma}} + \frac{A_K T}{A_L''}\left(\frac{\sigma}{1-\sigma}\right)[\otimes]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial \otimes}{\partial A_a}$$

respectively. Further differentiating T w.r.t. A_a we get,

(B.6)
$$\frac{\partial T}{\partial A_a} = \frac{A_L'}{A_K}\frac{\partial M}{\partial A_a}[\tau]^{\frac{\sigma}{1-\sigma}} + \frac{A_L' M}{A_K}\left(\frac{\sigma}{1-\sigma}\right)[\tau]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial \tau}{\partial A_a},$$

or alternatively,

(B.7)
$$\frac{\partial T}{\partial A_a} = \frac{A_L''}{A_K}\frac{\partial F}{\partial A_a}[\tau]^{\frac{\sigma}{1-\sigma}} + \frac{A_L'' F}{A_K}\left(\frac{\sigma}{1-\sigma}\right)[\tau]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial \tau}{\partial A_a}.$$

Using equations B.1 and B.6, equation B.4 can finally be written as follows

(B.8)
$$\frac{\partial M}{\partial A_a} = \frac{M\left[\left[\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P(1-\theta)A_K}{r}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right][\tau]^{\frac{\sigma}{1-\sigma}}[\odot]^{\frac{\sigma}{1-\sigma}}\right] + \left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P(\theta)A_L'}{w_m}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]\right]}{\left[1-[\tau]^{\frac{\sigma}{1-\sigma}}[\odot]^{\frac{\sigma}{1-\sigma}}\right]}.$$

Similarly, for female labor use, using equations B.2 and B.6, equation B.5 we can show that

(B.9)
$$\frac{\partial F}{\partial A_a} = F\frac{\left[\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P(1-\theta)A_K}{r}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right][\otimes]^{\frac{\sigma}{1-\sigma}}[\tau]^{\frac{\sigma}{1-\sigma}}\right] + \left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P(\theta)A_L''}{w_f}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]}{\left[1-[\tau]^{\frac{\sigma}{1-\sigma}}[\otimes]^{\frac{\sigma}{1-\sigma}}\right]}.$$

Proof of part (a):
Note that

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} = \frac{1}{T}\left[\frac{\partial F}{\partial A_a} - \left(\frac{F}{T}\right)\frac{\partial T}{\partial A_a}\right].$$

Inserting the expressions that appear inside the bracket as we have done under part (c) above, and simplifying it we get

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Leftrightarrow \left[\left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P(\theta)A_L''}{w_f}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right] < \left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right].$$

Once we make the substitutions of $\otimes$ and τ in the above expression and simplify the inequality further, we finally get the following condition:

$$\text{(B.10)} \qquad \frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Leftrightarrow \left[(\theta)^{\sigma}\left(\frac{w_f}{A_L''}\right)^{(1-\sigma)}\right] - \left[(1-\theta)^{\sigma}\left(\frac{r}{A_K}\right)^{(1-\sigma)}\right] < 0.$$

It is straightforward from above that

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Leftrightarrow \left(\frac{\theta}{1-\theta}\right)^{\sigma}\left(\frac{w_f A_K}{A_L r}\right)^{(1-\sigma)} < (\delta)^{(1-\sigma)},$$

and, given $\sigma < 1$, we can show that

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Leftrightarrow \delta > \left(\frac{\theta}{1-\theta}\right)^{\frac{\sigma}{1-\sigma}}\left(\frac{w_f A_K}{A_L r}\right) \equiv N.$$

Now, let us consider the case when $\epsilon > 1$. Using the expression of δ, the above condition becomes

$$\frac{1}{\alpha^{(\epsilon-1)}(w_m)^{(\epsilon-1)}}[\alpha^{\epsilon}(w_m)^{(\epsilon-1)} + (1-\alpha)^{\epsilon}(w_f)^{(\epsilon-1)}] > N^{\left(\frac{\epsilon-1}{\epsilon}\right)}.$$

Additionally, we write $N = \left[\frac{w_f}{w_m}\cdot Q\right]$ where we assume that

$$\text{(B.11)} \qquad Q \equiv \left(\frac{\theta}{1-\theta}\right)^{\left(\frac{\sigma}{1-\sigma}\right)}\left(\frac{w_m A_K}{rA_L}\right) > 1.$$

This implies that

$$\text{(B.12)} \qquad \frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \left(\frac{1-\alpha}{\alpha}\right)^{(\epsilon-1)}\left(\frac{w_f}{w_m}\right)^{(\epsilon-1)} > \frac{\left[\frac{w_f}{w_m}\cdot Q\right]^{\left(\frac{\epsilon-1}{\epsilon}\right)}}{1-\alpha} - \left(\frac{\alpha}{1-\alpha}\right).$$

If we make the following assumption

$$\text{(B.13)} \qquad (1-\alpha) < \left[\frac{w_f}{w_m}\cdot Q\right]^{\left(\frac{\epsilon-1}{\epsilon}\right)},$$

taking log on both the sides we get the following

$$\epsilon \cdot \log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right] > \log\left[\frac{w_f}{w_m}\cdot Q\right].$$

If the following restriction

$$\text{(B.14)} \qquad \left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right] < 1,$$

holds, we get

$$\text{(B.15)} \qquad \epsilon < \frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]}.$$

Note that if we want to accommodate the possibility for, $\epsilon > 1$, then we need the following

$$\frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]} > 1,$$

which is equivalent to $\alpha > 0$. Since, $\alpha > 0$ is assumed in our setup in the very beginning, we can argue that $\frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]} > 1$. If B.15 holds, we can substitute B.13 in B.12 which finally gives us the following

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \left(\frac{1-\alpha}{\alpha}\right)^{(\epsilon-1)}\left(\frac{w_f}{w_m}\right)^{(\epsilon-1)} > \frac{1-2\alpha}{1-\alpha}.$$

Taking log on both the sides we get the following,

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow (\epsilon-1)\cdot\log\left(\frac{1-\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right) > \log\left(\frac{1-2\alpha}{1-\alpha}\right).$$

Further, if we have

$$\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right) > 0, \tag{B.16}$$

we can show that

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon < \frac{\log\left(\frac{1-2\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)}{\log\left(\frac{1-\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)}.$$

If we want to have $\epsilon > 1$, then, we need the following

$$\frac{\log\left(\frac{1-2\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)}{\log\left(\frac{1-\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)} > 1,$$

and we can show that it is equivalent to $\alpha > 0$, thus the result is valid. Thus, if we have the following assumptions

$$\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right) > 1, \quad \left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right] < 1 \;\; and, \;\; \epsilon < \frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]},$$

we can assert that,

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon < \frac{\log\left(\frac{1-2\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)}{\log\left(\frac{1-\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right)}.$$

Thus, when we combine the two inequalities that we have for ϵ, then we have the following result

$$\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \min\left[\frac{\log\left[\frac{w_f}{w_m}\cdot Q\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{Q}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha}\cdot\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right]\right). \tag{B.17}$$

Proof of part (b):
It is straightforward from above that

$$\frac{\partial\tau}{\partial A_a} = \left[\frac{1}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)}(1-\sigma)A_a^{-\sigma}\right]$$

which implies

$$\frac{\partial \tau^{\frac{\sigma}{1-\sigma}}}{\partial A_a} = \left(\frac{\sigma}{1-\sigma}\right)[\tau]^{\frac{2\sigma-1}{1-\sigma}} \frac{\partial \tau}{\partial A_a} = [\tau]^{\frac{2\sigma-1}{1-\sigma}} \left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)} A_a^{-\sigma}\right].$$

Further, given

$$\frac{\partial \odot}{\partial A_a} = \left[\frac{1}{1-\theta}\left[\frac{PA_L'(\theta)}{w_m}\right]^{(1-\sigma)} (1-\sigma)A_a^{-\sigma}\right],$$

we have

$$\frac{\partial \odot^{\frac{\sigma}{1-\sigma}}}{\partial A_a} = \left(\frac{\sigma}{1-\sigma}\right)[\odot]^{\frac{2\sigma-1}{1-\sigma}} \frac{\partial \odot}{\partial A_a} = [\odot]^{\frac{2\sigma-1}{1-\sigma}} \left[\frac{\sigma}{1-\theta}\left[\frac{PA_L'(\theta)}{w_m}\right]^{(1-\sigma)} A_a^{-\sigma}\right]. \tag{B.18}$$

Using the expressions for M we have the following

$$\frac{\partial\left(\frac{A_L' M}{A_K}\right)}{\partial A_a} = \frac{\partial T}{\partial A_a}[\odot]^{\frac{\sigma}{1-\sigma}} + T\left[\frac{\partial [\odot]^{\frac{\sigma}{1-\sigma}}}{\partial A_a}\right] \tag{B.19}$$

and from the expression for T, we get

$$\frac{\partial T}{\partial A_a} = \frac{\partial\left(\frac{A_L' M}{A_K}\right)}{\partial A_a}[\tau]^{\frac{\sigma}{1-\sigma}} + \left(\frac{A_L' M}{A_K}\right)\frac{\partial \tau^{\frac{\sigma}{1-\sigma}}}{\partial A_a}. \tag{B.20}$$

Now, substituting B.18 and B.19 in B.20 and some further simplification guarantees that

$$\frac{\partial T}{\partial A_a} = T\frac{\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{PA_L'(\theta)}{w_m}\right]^{(1-\sigma)} A_a^{-\sigma}\right][\tau]^{\frac{\sigma}{1-\sigma}}[\odot]^{\frac{\sigma}{1-\sigma}} + \left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)} A_a^{-\sigma}\right]\right]}{\left[1-[\odot]^{\frac{\sigma}{1-\sigma}}[\tau]^{\frac{\sigma}{1-\sigma}}\right]}.$$

So we have,

$$\frac{M}{T}\frac{\partial T}{\partial A_a} = M\frac{\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{PA_L'(\theta)}{w_m}\right]^{(1-\sigma)} A_a^{-\sigma}\right][\tau]^{\frac{\sigma}{1-\sigma}}[\odot]^{\frac{\sigma}{1-\sigma}} + \left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)} A_a^{-\sigma}\right]\right]}{\left[1-[\odot]^{\frac{\sigma}{1-\sigma}}[\tau]^{\frac{\sigma}{1-\sigma}}\right]}$$

and,

$$\frac{F}{T}\frac{\partial T}{\partial A_a} = F\frac{\left[\left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{PA_L''(\theta)}{w_f}\right]^{(1-\sigma)} A_a^{-\sigma}\right][\tau]^{\frac{\sigma}{1-\sigma}}[\otimes]^{\frac{\sigma}{1-\sigma}} + \left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)} A_a^{-\sigma}\right]\right]}{\left[1-[\otimes]^{\frac{\sigma}{1-\sigma}}[\tau]^{\frac{\sigma}{1-\sigma}}\right]}.$$

Now,

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} = \frac{1}{T}\left[\frac{\partial M}{\partial A_a} - \left(\frac{M}{T}\right)\frac{\partial T}{\partial A_a}\right].$$

By replacing the expressions that appear inside the bracket on the right hand side and simplifying further we get

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Leftrightarrow\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P(\theta)A_L'}{w_m}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]<\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{PA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right].$$

Once we make the substitutions of $\odot$ and τ in the above expression and simplify the inequality further, we finally get the following condition:

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Leftrightarrow\left[(\theta)^{\sigma}\left(\frac{w_m}{A_L'}\right)^{(1-\sigma)}\right]-\left[(1-\theta)^{\sigma}\left(\frac{r}{A_K}\right)^{(1-\sigma)}\right]<0. \tag{B.21}$$

It is straightforward from above that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Leftrightarrow\left(\frac{\theta}{1-\theta}\right)^{(\sigma)}\left(\frac{w_m A_K}{rA_L}\right)^{(1-\sigma)}<(\Omega)^{(1-\sigma)},$$

and, given $\sigma<1$, we can show that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Leftrightarrow\Omega>\left(\frac{\theta}{1-\theta}\right)^{\left(\frac{\sigma}{1-\sigma}\right)}\left(\frac{w_m A_K}{rA_L}\right)\equiv Q.$$

When $\epsilon>1$, using the expression of Ω, the above condition becomes

$$\frac{1}{(1-\alpha)^{(\epsilon-1)}(w_f)^{(\epsilon-1)}}[\alpha^{\epsilon}(w_m)^{(\epsilon-1)}+(1-\alpha)^{\epsilon}(w_f)^{(\epsilon-1)}]>Q^{\left(\frac{\epsilon-1}{\epsilon}\right)}.$$

Given $Q>1$ so that $Q^{\left(\frac{\epsilon-1}{\epsilon}\right)}>1$, it is straightforward to show that the required condition becomes

$$\left(\frac{\alpha}{1-\alpha}\right)^{\epsilon}\left(\frac{w_m}{w_f}\right)^{\epsilon}>Q.$$

Taking log on both sides of the inequality we get the following

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Rightarrow\epsilon\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)>\log\left(Q\right).$$

Now if we have the following condition

$$\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)>1, \tag{B.22}$$

we can verify that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Rightarrow\epsilon>\frac{\log\left(Q\right)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)}.$$

When $\epsilon<1$, so that $Q^{\left(\frac{\epsilon-1}{\epsilon}\right)}<1$, we can show that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Rightarrow\left(\frac{\alpha}{1-\alpha}\right)^{\epsilon}\left(\frac{w_m}{w_f}\right)^{\epsilon}>Q,$$

and taking log on both sides of the inequality we get

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}<0\Rightarrow\epsilon\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)>\log\left(Q\right)$$

Now if B.22 holds, we guarantee that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon > \frac{\log(Q)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)}.$$

Since, this is the case where, $\epsilon < 1$, we must have the following

$$\frac{\log(Q)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)} < 1$$

which gives us the following

$$Q < \left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right). \tag{B.23}$$

Note that, this doesn't contradict with B.22 and given $Q > 1$. Therefore, given $Q > 1$, B.22, and B.23 hold, we can assert that

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon > \frac{\log(Q)}{\log\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)}.$$

We can express it in the set form as shown below

$$\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(\frac{\log[Q]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}, \infty\right). \tag{B.24}$$

Proof of part (c):
Note that

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{\partial\left(\frac{\frac{M}{T}}{\frac{F}{T}}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{T}{F}\left[\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} - \frac{M}{F}\cdot\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a}\right] > 0.$$

Given both T and F are strictly positive, the last inequality is equivalent to the condition

$$\frac{T}{M}\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a} > \frac{T}{F}\cdot\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a}.$$

Now, when we substitute the expressions for $\frac{\partial\left(\frac{M}{T}\right)}{\partial A_a}$ and $\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a}$ as presented above and simplify it significantly, we get the following inequality:

$$[\otimes]\left[\frac{A_L^{'}}{w_m}\right]^{(1-\sigma)} > [\odot]\left[\frac{A_L^{''}}{w_f}\right]^{(1-\sigma)}.$$

Once we replace the $\otimes$ and $\odot$ by their respective expressions and simplify it further, we guarantee that

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{\partial\left(\frac{\frac{M}{T}}{\frac{F}{T}}\right)}{\partial A_a} > 0 \Leftrightarrow \left[\frac{A_L^{'}}{w_m}\right]^{(1-\sigma)} < \left[\frac{A_L^{''}}{w_f}\right]^{(1-\sigma)} \Leftrightarrow \left[\frac{A_L^{'}}{w_m}\right] < \left[\frac{A_L^{''}}{w_f}\right] \qquad [\because \sigma < 1].$$

Further simplification shows that the last inequality becomes

$$\left[\frac{\delta}{\Omega}\right] > \left[\frac{w_f}{w_m}\right],$$

and, hence,

$$\left[\frac{1-\alpha}{\alpha}\cdot\frac{w_f}{w_m}\right]^{\epsilon} > \left[\frac{w_f}{w_m}\right].$$

Taking log on both sides we get the following:-

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0 \Rightarrow \epsilon \cdot \log\left[\frac{1-\alpha}{\alpha} \cdot \frac{w_f}{w_m}\right] > \log\left[\frac{w_f}{w_m}\right]$$

Given B.22, it can be verified that

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0 \Leftrightarrow \epsilon < \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}.$$

When we want to have the option of $\epsilon > 1$, then, we must have the following

$$\frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]} > 1,$$

which is equivalent to the condition

$$0 < \alpha < \frac{1}{2}. \tag{B.25}$$

Therefore, under the conditions B.22 and B.25, we guarantee that

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} > 0 \Rightarrow \epsilon < \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}.$$

We can express it in the set form as shown below

$$\frac{\partial\left(\frac{M}{F}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right). \tag{B.26}$$

All of these results and their respective assumptions must hold together as these results characterize the same aggregate economy. Note that the following assumptions we have made for the economy: B.11, B.13, B.14, B.22, B.23 and B.25. It is straightforward that B.11 and B.23 jointly subsume the restriction B.22 and imply the restriction $1 < Q < \left(\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right)$. This restriction taken together with B.14 actually sets a lower bound on $\frac{w_m}{w_f}$:

$$\frac{w_m}{w_f} > \max\left\{Q \cdot \left(\frac{1-\alpha}{\alpha}\right), \frac{Q}{1-\alpha}\right\}.$$

The assumption B.13 when $\epsilon < 1$ sets an extra lower bound on $\frac{w_m}{w_f}$:

$$\frac{w_m}{w_f} > \frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}},$$

which amounts to,

$$\frac{w_m}{w_f} > \max\left\{Q \cdot \left(\frac{1-\alpha}{\alpha}\right), \frac{Q}{1-\alpha}, \frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}}\right\}.$$

Moreover, $\frac{w_m}{w_f} > \frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}}$ implies that $\epsilon < \frac{\log\left[\frac{w_f}{w_m} \cdot Q\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{Q}{1-\alpha}\right]}$ and this restriction on ϵ is contained within the result $\frac{\partial\left(\frac{F}{T}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \min\left[\frac{\log\left[\frac{w_f}{w_m} \cdot Q\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{Q}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right]\right)$. However, the same assumption

B.13 along with $\epsilon > 1$ sets an upper bound on $\frac{w_m}{w_f}$:

$$\frac{w_m}{w_f} < \frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}}.$$

Note that given B.25, when $(1-\alpha)^2 < \alpha$, that is, $\alpha \in \left(\frac{3-\sqrt{5}}{2}, \frac{1}{2}\right)$, we have

$$\max\left\{Q \cdot \left(\frac{1-\alpha}{\alpha}\right), \frac{Q}{1-\alpha}\right\} = \frac{Q}{1-\alpha}.$$

The condition required so that $\frac{w_m}{w_f}$ is bounded inside a valid set is the following:

$$\frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}} > \frac{Q}{1-\alpha}.$$

Since $\epsilon > 1 \Leftrightarrow \frac{\epsilon}{\epsilon-1} > 1$ given B.25, $(1-\alpha)^{\frac{\epsilon}{\epsilon-1}} < (1-\alpha)$ holds true. On the other hand, given B.25, when $(1-\alpha)^2 > \alpha$, that is, $\alpha \in \left(0, \frac{3-\sqrt{5}}{2}\right)$, we have

$$\max\left\{Q \cdot \left(\frac{1-\alpha}{\alpha}\right), \frac{Q}{1-\alpha}\right\} = Q \cdot \left(\frac{1-\alpha}{\alpha}\right).$$

The condition required so that $\frac{w_m}{w_f}$ is bounded inside a valid set is the following:

$$\frac{Q}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}} > Q \cdot \left(\frac{1-\alpha}{\alpha}\right) \Leftrightarrow \alpha > (1-\alpha)^{\left(\frac{2\epsilon-1}{\epsilon-1}\right)}.$$

Taking $\log(.)$ on both sides and re-arranging the terms we get

$$\epsilon < \frac{\log\left[\frac{1-\alpha}{\alpha}\right]}{\log\left[\frac{(1-\alpha)^2}{\alpha}\right]} \quad \textit{where} \quad \frac{\log\left[\frac{1-\alpha}{\alpha}\right]}{\log\left[\frac{(1-\alpha)^2}{\alpha}\right]} > 1, \quad \textit{i.e.} \;\; \epsilon \in \left(1, \frac{\log\left[\frac{1-\alpha}{\alpha}\right]}{\log\left[\frac{(1-\alpha)^2}{\alpha}\right]}\right).$$

Therefore, the upper bound of the set containing $\frac{w_m}{w_f}$ is greater than its lower bound.

Since all of these results, namely B.17, B.24, and B.26, must hold simultaneously for the economy, the following characterizes the set of values possible for ϵ:

$$\epsilon \in \left(\frac{\log[Q]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \min\left[\frac{\log\left[\frac{w_f}{w_m} \cdot Q\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{Q}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right]\right) \tag{B.27}$$

where,

$$\frac{\log[Q]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]} < 1, \textit{and}, \quad \min\left[\frac{\log\left[\frac{w_f}{w_m} \cdot Q\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right] > 1.$$

The following is a separate conclusion regarding the set of possible values for ϵ when it is the case that $\alpha \in \left(0, \frac{3-\sqrt{5}}{2}\right)$, and, $\epsilon > 1$:

$$\epsilon \in \left(1, \min\left[\frac{\log\left[\frac{1-\alpha}{\alpha}\right]}{\log\left[\frac{(1-\alpha)^2}{\alpha}\right]}, \frac{\log\left[\frac{w_f}{w_m} \cdot Q\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{Q}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right]\right). \tag{B.28}$$

Thus we have shown, given labor and land are complementary to each other, when male wage rate is higher than the female wage rate and relative importance of male is higher than female in aggregate labor used with land to produce output, an economy can generate all the features depending on the elasticity between female and male labor, as mentioned in Proposition 1. The exact range of values of elasticity have been presented in B.27 and B.28. Hence the proof.

C Data Appendix

In this section we elaborate on the construction of our district level data set.

Construction of Variables

Soil texture

We elucidate how soil texture is classified by the National Bureau of Soil Survey (NBSS) in India. The NBSS defines three textural classes - Loamy, Clayey and Sandy. These three classes are derived from the detailed textural classification system followed internationally by the United States Department of Agriculture (USDA), which classifies soils into 12 textural classes depending on the presence of clay, silt and sand particles in the soil. These particles are defined on the basis of their diameter - clay (less than 0.002 mm), silt (0.002-0.05 mm) and sand (2-0.05 mm).[1] The 12 textural classes are: clay-loam, silty-clay-loam, silty-clay, sandy-clay, clay, silt, loam, silt-loam, sandy-clay-loam, sandy-loam, sandy, loamy-sand (USDA). NBSS further divides clay-loam into clay-loam (fine) and clay-loam (coarse). These 13 classes are then aggregated into three aggregate textural classes to classify a particular area as having Clayey, Loamy or Sandy soil. The aggregation is done in the following manner - Clayey (clay-loam (fine), silty-clay-loam, silty-clay, sandy-clay, clay), Loamy (silt, loam, silt-loam, sandy-clay-loam, sandy-loam, clay-loam (coarse)) and Sandy (sandy, loamy-sand). To elaborate, if soils in a given area fall in either of the classes aggregated under Loamy, then these soils are defined under the category of Loamy. The three aggregate classification categories are provided by the NBSS in their physical maps (created in early 1990's) for each polygon having similar properties (See Appendix Figure C.1). Data on the textural sub-categories are however not provided.

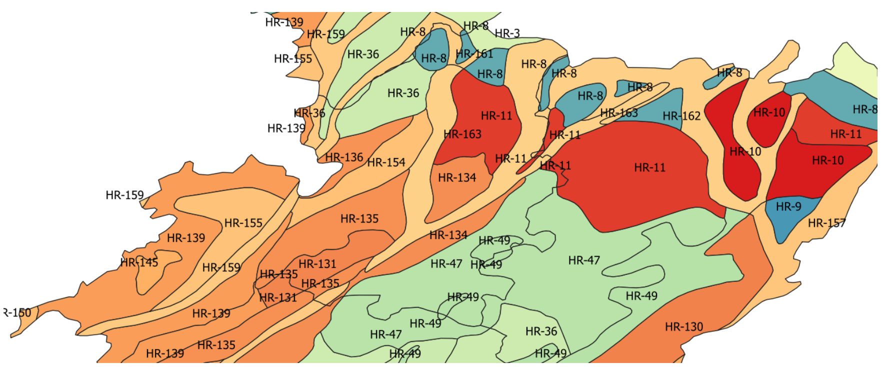


Figure C.1: NBSS soil map

Source: National Bureau of Soil and Survey, India.
Note: This map represents partial area of the state of Haryana in India. The soil within each shape, represented by a unique code, is classified as either clayey, loamy or sandy by the NBSS. The classification of the ph, depth and slope categories defined in Appendix Table A.3 are similarly provided for each polygon shape too.

We digitize these maps and attach the soil property of each polygon as provided by the NBSS.

The district boundaries are then overlaid on the digitized maps to obtain district-level proportion of area under loamy and clayey soils. For instance, consider the case with two polygons in a given district. Suppose both polygons have equal area, one is classified as loamy while the other is classified as clayey. Then the proportion of area under loamy soil is 50%. Since uptake of mechanization is more in loamy soils relative to clayey soils, *Loaminess* is defined as the difference between the proportion of loamy and clayey soils in a district. In this example, this will be zero, since equal area of a district is classified as Loamy and Clayey by the NBSS.

National sample Survey (NSS) on employment

We elucidate how employment is measured in the NSS. As discussed in the main paper, employment is captured both at the yearly level and at the daily level for the past week. Apart from employment, the sector of employment and the status of employment is also captured in the survey. Using the yearly definition, a person is classified as working in farm cultivation if she or he is employed in the farm sector (based on industry of employment) either in the principal or the subsidiary status. The principal status is the activity in which the person spent the most days in the preceding agricultural year. The subsidiary status is the activity in which a person spent more than 30 days but less than 6 months in the preceding year. We sum up the number of workers, after multiplying each worker with the individual weight provided in the NSS, for each district to get an estimate of the total number of individuals employed in the farm sector at the district level. To further classify a person as a family worker or hired laborer we use the status of employment. The status of an employed individual is defined as - self-employed (worked as own account worker or an employer or an unpaid family worker), casual wage labourer (private work) or regular salaried (worked as regular salaried/ wage employee). In the farm sector there are almost no regular salaried jobs and workers are either classified as self-employed (family workers) or casual laborers (hired workers).[2] If an individual is classified as self-employed (casual laborer) in farming sector in either the principal or the subsidiary status then she or he is counted in the number of individuals who worked as family (hired) labor in our dependent variable.

Input census

The survey rounds of 1997-99, 2007 and 2011, correspond most closely to the NSS employment data. Initial rounds were not evenly spaced every 5 years.[3] We detail the classification of implements from all sources of power by their operation type in the following manner. Primary tilling equipment consists of wooden plough, mould board plough, tractor driven mould board plough, rotavator, cultivator. Secondary tilling equipment consists of hand-hoe, wheel-hoe, blade-hoe, levelling kahan, animal driven wooden plough, disk harrow, Tractor Driven Disc Harrow, Tractor Driven Leveller, cagewheel. Sowing equipment includes paddy drum seeder, paddy transplanter, seed planter, tractor driven planter. Weeding equipment includes hand-hoe, wheel-hoe, blade-hoe, cono-weeder, paddy weeder,garden fork, cultivator triphali. Harvesting and threshing equipment includes pedal operated thresher, olpad thresher, reaper, power thresher, combined harvester (trailed), combined harvester (self propelled), reaper. These are further sub-classified by sources of power - hand operated, animal operated and power operated.

Other agricultural inputs

Annual fertilizer consumption (in kg) of the three main types (nitrogenous, potassium and phosphorous) has been obtained from Centre for Monitoring Indian Economy's database constructed from various publications of Fertilizer Association of India. The annual consumption, at the district level, is divided by total area under cultivation to allow for comparison across districts. The variable is measured as kilograms of fertilizer used per hectare of cultivated area.

Crop composition

Data on area under various crops is obtained from the Ministry of Agriculture's Annual District-wise Crop Production Statistics for years between 1998 and 2011. The gross cropped area ('000 hectares) under nearly 60 different crops is consolidated into the following: wheat, rice, coarse cereals, pulses, oil seeds, fruits & vegetables, spices and condiments, sugarcane, cotton, other fibre crops and other plantation crops. The proportion of cropped area under each of the above is then calculated at the district level by dividing area under each category by the total cropped area.

Climate

Daily gridded datasets for rainfall (0.25ox0.25o grid) and temperature (1ox1o grid) have been obtained from the India Meteorological Department (IMD). The gridded datasets are overlaid over a district level political map of India. District averages for daily rainfall (mm) and average temperature (^{o}C) are calculated by taking a weighted average of values for grid points lying within a district. The weight given to each grid point is the fraction of the district's area lying in the grid having that grid point as its centroid. Finally, the variable for annual rainfall is constructed by summing up daily rainfall and for yearly mean temperature by taking the average over all the days in the agricultural year (June to May). The average annual daily temperature is constructed similarly by taking the mean of daily temperatures for the agricultural year.

Other agricultural controls

The Ministry of Agriculture's 'Land Use Statistics' publication is used to calculate the fraction of irrigated area for each district by dividing the total irrigated area by total cropped area in a district. Using data on agricultural landholding from the Input Census, we construct average landholding size (hectares) by dividing total area under landholdings by the total number of operational agricultural holdings in a district. The proportion of urban population in a district is calculated from district population tables available in the Census (2001 and 2011).[4]

Socio-demographics

The proportion of population that belongs to Scheduled Caste, Scheduled Tribe, Other Backward Castes and general category, along with religious composition of Hindus, Muslims, Christians and Others and education of men and women in a district is constructed from National Sample Survey (NSS) rounds (55, 64 and 68). For each of these characteristics, a weighted sum of individual characteristics in each district (for population aged 15-65) is taken and divided by the total population in that district to give the proportion in each category for that year in the NSS.

Development controls

Proportion of villages with a paved approach road in a district is constructed by counting the number of villages having a paved approach road and dividing by total number of villages in a district (Census 2001 and 2011). Gridded nightlights data has been obtained from the Defence Meteorological Satellite Program (DMSP) for the years 1992-2013. Each pixel in this grid has a 6-bit value (between 0 and 63) that represents relative nightlight brightness. The grid containing annual average values of nightlight is superimposed on a district level map of India. The annual district average nightlight luminosity is obtained by averaging over the pixels within a district boundary.

District mapping

Some districts were excluded from the analyses due to small agriculture sector or due to lack of information on important variables. The state of Goa and the Union Territories of Delhi, Chandigarh, Pondicherry, Daman & Diu, Dadra & Nagar Haveli, Lakshadweep and Andaman & Nicobar Islands are excluded from the dataset because of high urbanization and small rural agricultural sector. West Bengal, the north-eastern states of Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, Sikkim, northern state of Jammu & Kashmir (presently a Union Territory) are excluded due to lack of availability of detailed soil maps for these states. The remaining districts (418 in number) were merged into the parent districts to take into account the district splitting over time giving a total of 1254 district year observations.

Additionally, the district level mechanization data for the states of Bihar and Maharashtra was collected only in 2011 and hence these states are dropped from the analyses for the years 1999 and 2007. This exclusion leads to a drop of 162 district-year observations. Around three districts in Gujarat were not surveyed for employment data collected in 1999 and two districts from Himachal Pradesh are also excluded due to missing soil characteristics for these areas. This leads to exclusion of these districts from year 1999 leading to a further loss of 9 observations. The final dataset has 1083 district year observations. In the regression specifications which control for initial employment in 1993, 6 observations are missing due to a few districts being absent in the National Sample Survey data for 1993. The baseline 2SLS specification thus has 1077 district-year observations.

D Estimate Bounding Exercise

We implement the procedure suggested in Conley et al. (2012) for obtaining bounds on linear-IV estimates. The method is described below. Consider the following system of equations

$$Y = X\beta + Z\gamma + u$$

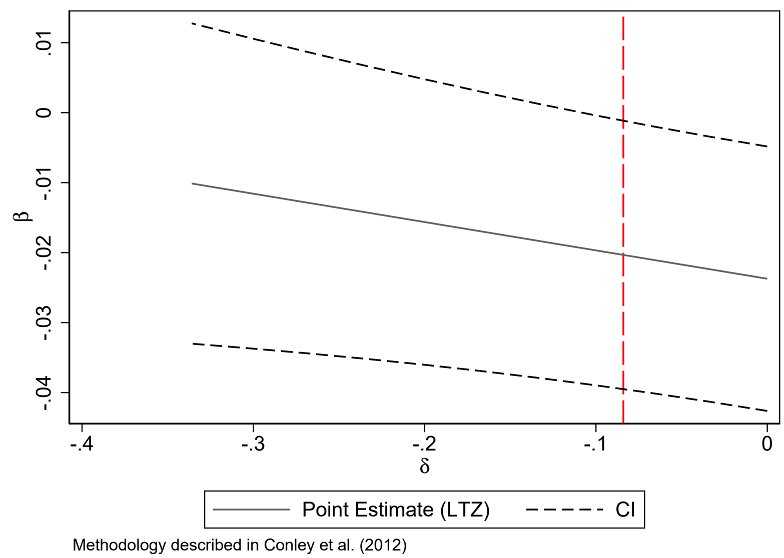
$$X = Z\pi + v$$

The identification assumption under the IV methodology is that $\gamma = 0$. In the method proposed by Conley et al. (2012), the exclusion restriction is allowed to fail by specifying priors over it under exact identification. The implementation of this procedure needs assumptions regarding the range of values that γ can take (a prior over the distribution of γ). This requires a measure of the direct effect of the IV on the outcome variables. We infer this by examining the reduced form effect of the IV on labor use in 1993 i.e. before the push for farm mechanization occurred in India.[5] Thus, using the estimates in Table 3, our inferred estimate for the direct effect of loaminess on female labor use ($\hat{\gamma^F}$) is -0.084 while that on male labor use ($\hat{\gamma^M}$) is 0.014, albeit these are insignificant.

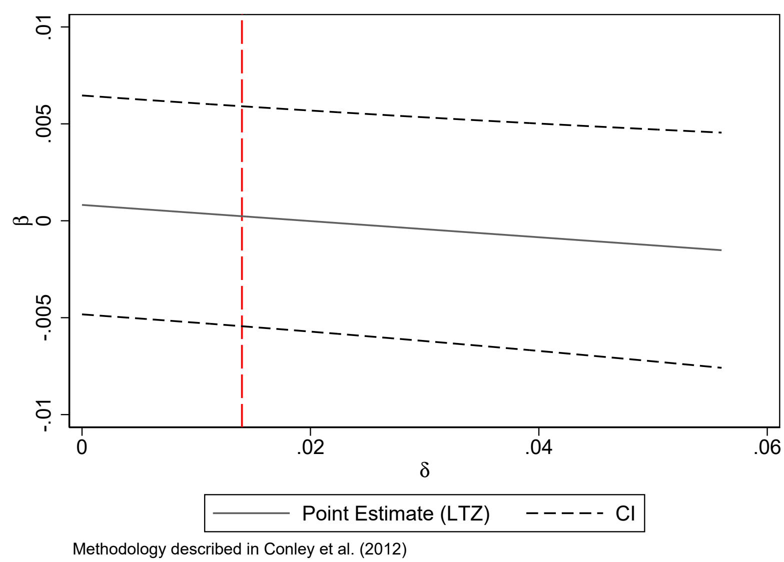
We use both the methods proposed by Conley et al. (2012). First, we use a lower to zero (LTZ) approach wherein bounds on $\hat{\beta}_1^g$ are estimated across a range of priors (where g represents gender so $g \in F, M$). Here, the assumption that γ^g=0 is replaced with an assumption that $\gamma^g \sim$ F (an arbitrary distribution). We make two further assumptions to arrive at the distribution for γ^g. Consider the case when $g = F$. We assume that γ^F lies in a range of values between 0 and -0.168, thus the mid value of γ^F for this range is -0.084, the estimated mean. We consider only the negative ranges of γ^F because the concern is that the IV may have a direct negative effect on female labor use. Assuming $\gamma^F \sim U(0, \delta)$, Figure D.1, Panel (a), plots the confidence interval bounds for a range of assumed values of δ, shown on the x-axis.[6] It can be seen that as values of δ decrease, the bounds become imprecise. For values of δ <-0.135 or a larger than 13.5% direct decrease in female labor use per hectare due to the IV, the effect of mechanization on female labor use becomes insignificant.

Next, consider the case when $g = M$. We make similar assumptions here. One, that γ^M lies in a range of values between 0 and 0.028, thus the mid value of γ^M for this range is 0.014. Here, we consider only the positive ranges of γ^M because the concern is that the IV may have a direct positive effect on male labor use, resulting in no impact of mechanization on male labor use using the IV estimate. Again, assuming $\gamma^M \sim U(0, \delta)$, Figure D.1, Panel (b), plots the confidence interval bounds for a range of assumed values of δ. It can be clearly seen that the effect of mechanization on male labor use remains insignificant for values as large as 6% direct effect of the IV on the male labor use.[7]

We now use the second approach proposed by Conley et al. (2012). Here, we produce a union of confidence intervals on $\hat{\beta}_1^g$ for multiple models, where γ^g lies in the range [γ^g_{min}, γ^g_{max}]. This approach is called the Union of Confidence Intervals (UCI) approach, as the final bound consists of the union of all confidence intervals in the assumed range of γ^g. We calculate the UCI for the range, where $\gamma^F \in [\hat{\gamma^F}, 0]$ and $\gamma^F \in [2 * \hat{\gamma^F}, 0]$, and obtain (-.043,0) and (-0.043, 0.006) as the union of all confidence intervals, respectively.[8] Similarly, for men we find that when $\gamma^M \in [\hat{\gamma^M}, 0]$ and $\gamma^M \in [2 * \hat{\gamma^M}, 0]$, the union of all confidence intervals are (-0.006, 0.006) and (-0.007, 0.006) respectively. Thus, the effect of mechanization on female labor use continues to be negative and statistically significant at reasonable level of violation when the minimum value of γ^F is equal to -0.084. On the other hand, the estimates for men continue to be insignificant.[9]



(a) Female Labor



(b) Male Labor

Figure D.1: Bounds on IV estimates on female and male labor use: LTZ (empirical distribution)

Note: The figure plots the 90% confidence bounds obtained on the effect of toilet construction on log of assaults as the dependent variable (β_1) using the linear-IV approach. See Conley et al. (2012) for the details of the procedure. The vertical dashed line indicates the point at which the preferred estimate lies at the centre of the assumed support for γ^F and γ^M, in Panel (a) and (b), respectively. The LTZ approach here assumes that the sign on the instrument when included in the structural equation is distributed as $U(0, \delta)$.

Notes

[1]Sand is further divided into classes (very fine to very coarse) depending on the diameter.

[2]This classification is decided based upon the majority of the time spent across these employment categories. For instance, if an individual only worked on her or his family farm either as an employer or an unpaid family worker then that individual would be classified as self-employed. If an individual worked on both family farm as well as a casual laborer on another farm, then based on which activity more days were spent, she or he would be classified in either principal or subsidiary status. For instance, if an individual worked mostly on his farm and spend only a month working as a casual laborer then she or he will be classified as self-employed in principal status and casual laborer in subsidiary status.

[3]The survey round to be conducted in 1996, was spread over 1997-99 across different states of India. The latest year for which district level data is available is 2011-12. Another round was held in 2001-02 but it has several missing observations and inconsistencies for landholdings cultivated for a few states. Also, this round was held three years before the nearest employment round of 2004-05. Hence, we do not include the input data from 2001-02 in our analyses.

[4]For variables used from Census data, the values for 1999 and 2007 are imputed by fitting a linear annual growth rate of the variable between 2001 and 2011 for each district and then predicting them for 1999 and 2007.

[5]There are no existing studies that we can rely on for this estimate. In this case, it recommended to compute this using a plausible placebo test (Conley et al., 2012).

[6]When $\delta = 0$ the bounds refer to the confidence interval for the original IV estimate.

[7]It remains insignificant even upto 50% direct marginal effect.

[8]This choice is based on the initial implementation in the Conley et al. (2012) paper and on the existing literature (Bhalotra and Clarke, 2020), which uses interval such that $\hat{\gamma}$ lies in the middle of the interval.

[9]Alternatively, Nevo and Rosen (2012) propose a bounding exercise based on correlation between the endogenous variable, the IV and the error. To implement this, one requires to know the direction of correlation between the endogenous variable and the error term for female and male farm labor use. These are discussed in Section 5 when discussing the OLS estimates. For female labor use, given the concern that the IV is negatively correlated with the error, and that mechanization is positively correlated with the error, and the IV and mechanization are positively related, the true parameter will be bounded by the IV and the OLS estimate. Using a similar argument, the bound between the OLS and the IV estimate will hold for men too. Hence, the Nevo and Rosen (2012) procedure is not very informative in our context.

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