Gendering Technological Change: Evidence from Agricultural Mechanization

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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 has led to significantly greater decline in women's than men's labor on Indian farms. Reduced demand for labor in weeding, a task that requires precision and is thus more often undertaken by women, explains our findings. The estimates suggest that increased mechanized tilling led to a more than 22% fall in women's agricultural labor in India, with no accompanying increase in their non-farm sector employment, during 1999-2011. Our results highlight the gendered impact of technological change in contexts where there is sex-specific specialization of labor.

JEL classification: J16, J23, J43, O33
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1 Introduction

Existing literature has focused on the effects of technological change on skilled vs. unskilled labor when they are imperfect substitutes and technology complements skilled labor (Acemoglu & 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 (Burton & White (1984); Laufer (1985); Jacoby (1991); Skoufias (1993); Quisumbing (1996); Doss (1999)). When women perform tasks which require different skills, and which have limited substitutability with the tasks typically performed by men, technological change can have disproportionate gender impacts. In this paper we use data on farm labor and input usage during 1999-2011 in India to analyse the effect of increased use of farm machinery on men's and women's labor use in agriculture.

We focus on technological change in agriculture during a period of rapid farm mechanization. Using exogenous variation in the difference between loamy and clayey soil shares in a district, we first show that machine usage in tilling of land is significantly determined by the extent of loaminess of the soil (Bigot *et al.* (1987)). Since loamy soil, relative to clayey, is more amenable to deep tillage (Wildman (1981); Basant (1987)), it is likely that there is greater use of mechanized tools to aid in land tilling. We then utilize this predicted, exogenous variation in mechanization in the first stage to analyse its impact on men's and women's labor used on the farm in a two stage least squares specification.

We find that a one percentage point increase in mechanization decreases female labor used per hectare by 0.7%. Men's labor also falls by 0.1% per hectare, but insignificantly. Thus the observed 32 percentage point increase in mechanization during 1999-2011 led to more than 22% overall reduction in women's labor use in agriculture. This 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. 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, district specific employment trends due to differences in initial labor use and state specific time fixed effects.

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. With greater adoption of power operated implements in land tilling, a task that requires physical strength and therefore more male vis-a-vis female labor, 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 these implements than women, any fall in men's labor usage may be mitigated. On the other hand, adoption of machines in tilling has a cascading effect on demand for labor in downstream operations which require more precision and less physical strength - tasks in which women specialize. Specifically, better quality tillage reduces weed growth, lowering the demand for weeding labor. Hence, we find that the overall effect of mechanization on women's labor usage 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. The observed decline in labor force participation of women in rural India during this period, thus, is likely driven by the fall in their labor use in agriculture.

Our theoretical model, where male and female labor are considered separate inputs in agricultural production, explains the above findings. We not only show that technological change can 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. Specifically, we illustrate that women's labor can fall more than that of men's when there is imperfect substitutability between the two types of labor inputs (a characteristic feature of agricultural production processes due to the gendered division of labor across tasks) and more weight is placed on the male labor in the production process (a characteristic in line with greater use of male labor and complementarity between male labor and tilling machinery in agriculture).

Previous research has looked at technological innovations in agriculture brought about by the advent of the green revolution (primarily in the 1960s) in developing countries (Foster & Rosenzweig (1996)). These involved introduction of improved seed varieties (Bustos *et al.* (2016); Emerick *et al.* (2016)), increased fertilizer (Beaman *et al.* (2013)) and irrigation use. While these technological changes increased agricultural productivity (Pingali (2012)), they also carried implications for human capital investments (Rosenzweig (1990); Behrman *et al.* (1999)) and household health (Brainerd & Menon (2014)) which could differ by gender. However, the literature that looks at technological changes due to agricultural mechanization has largely studied its implications for labor use, considering labor as a homogeneous entity (Binswanger (1978)). For instance, in a review of 24 studies on labor use of farm households, Norman *et al.* (1988) find that all except two reported lower labor use per hectare of crop production for farms which used tractors as opposed to draft animal farms. Twelve of these studies report reduction in labor use by 50% or more.

The consensus is that mechanization in agriculture has often been labor substituting (Binswanger (1978); de Janvry *et al.* (1989)).[1] Consistent with the literature, adoption of machine tools in Indian agriculture, often powered by tractors, has been accompanied by a reduction in farm employment in rural India.[2] But insights into whether mechanization affects women's and men's labor differently 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

[1] Notably, unlike green revolution, the effect of mechanization on farm productivity is debated (Pingali (2007)). If farm productivity increases simultaneously with mechanization then total farm labor use may also rise to the extent yield and multiple cropping increase. However, there is inconclusive evidence of an increase in yields or acreage due to the adoption of power-intensive mechanization, such as tractors. There is however broad consensus on labor use per unit cultivated land, as discussed above.

[2] A few studies that do analyse impacts of increased machinery, e.g. tractors, on farms during the green revolution in India focus on land productivity, labor use per hectare and total labor use (Binswanger (1978)) by comparing farms over time or farms using tractors versus those that did not at a point in time to show that labor use per hectare is lower on farms that use tractors versus that do not. However, since this period was also accompanied by large changes in other inputs like fertilizers and irrigation, these conclusions are confounded.

with machinery also differs (Boserup (1970); Laufer (1985)) in agricultural production.

Agricultural technology on Indian farms has undergone a rapid change with increased machine usage over the last two decades. Rising use of tractors is an indicator of extent of mechanization since tractors provide power to most farm based machine tools. Between 1999-2011 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. At the same time, during 1999-2011 the proportion of working age adults employed in rural farm sector fell by 11 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 labor force participation in rural India over the last three decades (Afridi *et al.* (2018)) - from 49% in 1999 to 40% in 2011 and further to 28% in 2017 (Periodic Labor Force Survey). A large part of this decline has been due to a reduction in women's employment in agriculture with no commensurate increase in their employment in other sectors.[3]

The literature on the determinants of women's work, in general, and the gender impact of technological change, in particular, has focused primarily on home production since women spend disproportionately more time on household chores (Greenwood *et al.* (2005)). There is near absence of research on the gender differentiated impact of changes in market production technology. This lacuna is particularly striking in agriculture where women comprise, on average, 43% of the labor force in developing countries - ranging from 20% in Latin America to 50% in Eastern Asia and sub-Saharan Africa (FAO (2011)) - and there exists sex-specific specialization of tasks. In this context, the gendered effects of mechanization on labor likely depend both on which agricultural operations are mechanized (direct effects) and its spillover impact on other tasks (indirect effect).

[3] Around 39% of the working age women were employed in the farm sector in rural India in 1999 and this fell to 27% in 2011. However, their employment in the construction sector increased from 1% in 1999 to 5.4% in 2011, in the services sector increased from 3% to 3.5% while that in the manufacturing sector it was stable at 4% (National Sample Survey, various rounds). Research has focused on supply side factors such as increase in real household incomes, increased home productivity and social norms as explanations for the observed decline in women's LFP (e.g. Afridi *et al.* (2018) and Afridi *et al.* (2019)).

Our study contributes to several strands of research. First, and more broadly, the further 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, since our context is agriculture, a sector that dominates low-income economies, it aids our understanding of how structural transformation induced by technological change in agriculture can potentially exacerbate existing gender inequities in labor force participation. Finally, and more narrowly, this study broadens our understanding of the potential reasons for the decline in women's workforce participation in rural India, a topic of fierce debate but limited consensus, in recent years (Afridi *et al.* (2018)).

The remainder of the paper is organized as follows. We first describe the nature of the production process in agriculture (Section 2) followed by a simple theoretical model that analyses the potential gender impacts of technological change in agriculture (Section 3). Section 4.1 describes the data sets used and the construction of variables. The empirical strategy is discussed in Section 4.2 and our findings in Section 5. We discuss the results in Section 6 and conclude in Section 7.

2 Background

Agricultural mechanization is defined as a process where the source of power changes from simple hand tools and animal draught power to mechanical power. In order to assess the potential channels through which mechanization can affect labor use in agriculture, it is important to understand the organization of the agricultural production process which consists of multiple operations (Skoufias (1993)). These operations can be broadly classified into three stages: Stage 1 - land preparation through 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. 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 an increased use of machinery in downstream tasks, particularly for Stage 3 harvesting operations. Since Stage 2 operations require less physical strength and more precision they are usually less likely (or the last) to be mechanized. This pattern of adoption of mechanical technologies in agriculture has been observed for both the developed as well as the developing countries (Binswanger (1986); Pingali & Hossain (1998)).

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 & Schindler (1999)). Loamy soils are more amenable to deep tilling (Wildman (1981); Basant (1987)) 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. Historically, men prepare land in both deep and shallow tilling areas due to their biological advantage over women (Giuliano (2017)). But areas with more loamy soil content are more likely to use deep tilling/ploughing implements due to greater tilling depth requirement (Carranza (2014)). The loamy-clayey content of the soil could, therefore, also affect the adoption of power operated machines, specifically in tilling.

In general, adoption of machines can either displace or augment labor depending on the operation for which they are used and their impact on agricultural productivity.[4] In

[4] 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 like land preparation, sowing, weeding and harvesting can reduce the demand for labor (Pingali (2007)).

this paper we specifically look at mechanization in Stage 1 of the agricultural operations i.e. tilling. In this operation, the ploughing machines for both primary and secondary tilling are driven by either a tractor or a power tiller.[5] Therefore, it is likely that usage of ploughing machines for secondary tilling operation is linked to adoption of ploughing machines in primary tilling operation, since the largest fixed cost of mechanization involves tractor purchase.[6] An increased uptake of machines in tilling can have direct and indirect effects on labor use. The direct effects can occur if labor use in tilling is substituted with the machine. The indirect effects can occur if improved tilling quality due to machine adoption, lowers the demand for labor in other tasks like sowing, weeding and harvesting.[7]

The third and final relevant characteristic is the gendered division of labor in agriculture - men and women perform different tasks due to intrinsic, including biological, factors. They are, hence, imperfect substitutes for each other in agricultural production (Jacoby (1991); Skoufias (1993); Quisumbing (1996)). 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 like sowing/transplanting and weeding (Mahajan & 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 in 1999-2011 (see Table A.1 in Appendix A). These data suggest that men are significantly more likely to be used for tilling operations in Indian agriculture, relative to other operations.

[5] These machines include mould board ploughs, rotavators and cultivators. Majority of the machines in secondary tillage (disc harrow, cagewheel and leveller) are also tractor or power tiller drawn.

[6] Currently, the average tractor price in India is USD 7000 while the cost of tilling attachments lies between USD 200 to USD 600. On the other hand, for the harvesting operation, harvesters and threshers are usually self propelled machines, except for combine harvester that trails behind the tractor. Combine harvesters are a small proportion of total mechanical harvesting equipment in India (approximately 10% according to the Input Census). Sowing and weeding, relatively more precision based operations, have not seen a large uptake of mechanized implements.

[7] Source: FAO.

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. It is, therefore, imperative to analyse the impact of technological change on overall labor use as well as by operation. These characteristic features of the agricultural production process can lead to gender differentiated impacts of mechanization of Stage 1 agricultural operations.

In this paper we focus on the increased machine uptake in Indian agriculture during 1999-2011 due to two reasons: first, this period saw a much larger increase in mechanical power in Indian agriculture as compared to previous decades and second, detailed district level data are not available for earlier years. 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)).[8] This rise can be attributed to farm mechanization policies and programs introduced since 2000 which have offered subsidies on farm equipment purchase.[9] Further, a sharp increase in rural agricultural credit provision to farmers in the 2000s also boosted farm machinery uptake.[10] We thus focus on the labor impacts of increased adoption of mechanical power during the 2000s - the decade which saw the fastest rate of farm mechanization in India. In the next section, we use a simple theoretical model, to evaluate the potential effects of mechanization on labor use in agriculture.

[8]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).

[9]The Macro Management of Agricultural (MMA) scheme, launched in 2000 and further revised in 2008, had a sub-scheme on agricultural mechanization which subsidized farm equipment by 25-50% of cost of purchase.

[10]The annual growth of bank credit extended to agriculture in the 90s had slowed down to 1.8 per cent per annum between 1990 and 2000. A slew of policy measures were launched in late 1990s to increase farmer credit access from institutional sources, including both short and long term loans. For instance, Kisan Credit Cards were launched in 1998, National Agriculture Policy Statement in 2000 envisaged a special agricultural credit plan and the Doubling of Agricultural Credit Policy in three years (2003-04) to revive agricultural lending. Consequently, between 2000 and 2006, agricultural credit grew by 20.5 per cent per annum.

3 Theoretical model

We model an agricultural sector where the final good (Y_a) is produced using two inputs, namely aggregate labor (L_a) and aggregate land (T_a). We assume that the production of the final good follows a Constant Elasticity of Substitution (CES) technology of the following form:

$$Y_a(L_a, T_a) = A_a[\theta(A_L L_a)^{\frac{(\sigma-1)}{\sigma}} + (1-\theta)(A_K T_a)^{\frac{(\sigma-1)}{\sigma}}]^{\frac{\sigma}{(\sigma-1)}}. \tag{1}$$

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)).

Following the above discussion of the agricultural production process, we assume that total labor L_a is composed of female labor (F_a) and male labor (M_a). Since agricultural operations are gender specific, aggregate labor L_a is assumed to combine F_a and M_a in the following way:

$$L_a(F_a, M_a) = [\alpha F_a^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha)M_a^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{\epsilon}{(\epsilon-1)}}. \tag{2}$$

The elasticity of substitution between female and male labor is represented by $\epsilon > 0$ and their relative importance is denoted by the parameter $\alpha \in (0,1)$.[11]

Since the agricultural sector is assumed to be competitive in nature, 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. Let us denote the equilibrium wages of female and male labor by w_F and w_M, respectively, and the factor price of land by R. Further, the market

[11] 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.

price of the final agricultural product is denoted by P_a.[12] Given these notations, the profit maximizing conditions with respect to the three factors, F_a, M_a and T_a are as follows:

$$P_a \frac{\partial Y_a}{\partial F_a} = w_f, \tag{3}$$

$$P_a \frac{\partial Y_a}{\partial M_a} = w_m, \tag{4}$$

$$P_a \frac{\partial Y_a}{\partial T_a} = R. \tag{5}$$

We now assume a Hicks neutral productivity change due to mechanization, since machine use can plausibly increase the productivity of both labor and land. In this setup, under some reasonable assumptions, we derive the conditions under which mechanization of the production process, precisely a change in A_a, can decrease labor use per hectare and, crucially, has a gender differential effect. First we assume that male wage w_m is higher than the female labor w_f, that is, there is a gender difference in the wage rate. This is a well established characteristic of agricultural labor markets (Lagakos & Waugh (2013)) which also holds in the Indian context (Mahajan & Ramaswami (2017)). Second, 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. Given these fairly reasonable assumptions, we derive the following proposition (Proof in Appendix B).

Proposition 1 *Under the competitive equilibrium,*

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

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

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

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

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

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

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

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

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.34 and B.35 in Appendix B).*

Part (a) and (b) above guarantee that both female and male labor fall due to a change in technology, followed by (c) which derives the conditions under which the relative use of male and female labor can change differentially, i.e. the fall in female labor due to mechanization is higher. These three results hold jointly 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).[13] Thus, when male and female labor are neither perfect substitutes nor perfect complements, the above results hold true.

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

[13] This has precisely been presented in conditions B.34 and B.35 in Appendix B. Note that all the terms inside the min function are greater than one, hence, upper bound is strictly greater than one.

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. This is in concordance with the existing literature which argues that male and female labor are likely to be imperfect substitutes given the gendered division of labor observed in agriculture (Jacoby (1991); Skoufias (1993); Quisumbing (1996)). Moreover, greater weightage to male labor in the agricultural production process may be justified if men are intrinsically or biologically more suitable to the production process which undergoes technological change.

Next, we describe our data and discuss the observed patterns in mechanization across operations and agricultural employment in India and the empirical strategy.

4 Data and Methodology

4.1 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 1083 district-year observations.[14] Construction of our main variables of interest and the data sources is briefly described below. The details of data construction are provided in Data Appendix C.

Farm Labor Use: We use 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).[15] Our main dependent variable - number of workers per hectare of cultivated land in a district, is obtained by dividing the number of individuals engaged in farm cultivation (of age 15-65 years) in a district by the total cultivated area

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

[15] Since all districts are surveyed every quarter, we capture the entire agricultural season.

in that district in a year. This measure, standard in the literature on the effects of mechanization on labor demand (Pingali (2007)), normalizes the total labor use by cultivated area since cultivated area is likely endogenous.[16] We also measure agricultural employment in different operations (tilling, sowing, weeding, harvesting and others) - as the total number of workdays in a week that workers are engaged in a given agricultural operation per hectare of cultivated land in a district. The NSS surveys capture the entire agricultural year in each district, and thus cover all seasons.

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. 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. It also classifies all implements into three categories depending on the source of energy usage - hand, animal and power operated.[17] We further classify the implements used by agricultural operation and 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, therefore, define mechanization as the sum of the area cultivated under electric and mechanical power operated primary and the secondary tilling equipment multiplied by 100. Each unit increase

[16] 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. 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. The total cultivated area is obtained from the input census.

[17] The power operated implements are those which require electrical or mechanical source for drawing power and thus correspond to machine uptake in agriculture.

in mechanization thus measures 1 percentage point increase in mechanized tilling intensity.[18]

Soil characteristics: We digitize the National Bureau of Soil Survey's soil maps (designed during the mid 1990's for various states of India) using Geographic Information System (GIS). The district boundaries were overlaid on the digitized maps to obtain district-level soil characteristics, such as soil texture, depth, slope and pH content. These were constructed by summing up the area in a district having a particular soil characteristic and dividing it by the total area of the district. The main variable of interest here is the difference between loamy and clayey soil shares since this characteristic of the soil influences the required depth of tillage and thereby take-up of machinery in Stage 1.

Other district characteristics: We compile data for a host of other district level agricultural characteristics such as average landholding size, climate, irrigation, crop composition and fertilizer usage using a variety of data sources. Variation in crop composition across regions can directly impact labor use in agriculture (Bardhan (1974); Chin (2012); Mahajan & Ramaswami (2017)) and hence we control for it in all our specifications. Fertilizer use can potentially be endogenous to mechanization in an area, therefore we control for fertilizer use lagged by an year. We use the NSS rounds, the decennial Census (2001 and 2011) and Defence Meteorological Satellite Program (DMSP; 1992-2013) to measure various socio-economic characteristics of a district - religion, caste, road infrastructure and economic activity through night lights. The detailed construction of these variables is discussed in Data Appendix C.

[18]The input census gives the total area cultivated under a particular machine in a district. We further classify these machines by stage of operation. Therefore, if a parcel of land undergoes primary tilling using 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 figure out how much land has been double counted since plot level data is not available. Our measure of mechanization hence should be interpreted as the intensity of mechanization in tilling.

Table 1 lists the summary statistics for farm employment and mechanization for each year in our analyses.[19] Clearly, female labor use has fallen over time and male labor use has not changed much. Figure 1 plots the change over time by indexing the labor use in each year by the labor use in year 1999 for that category. It again reflects the same trends in labor by gender as seen in the summary statistics. We observe a secular fall in women's labor use per hectare of land cultivated over time but men's labor use per hectare has not fallen but rather plateaued in the recent years.

The above trend in farm labor use has been accompanied by a rise in agricultural mechanization in India. Table 1 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 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 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. We see that the largest increase in use of mechanical power has been in the tilling operations in Stage 1, followed by harvesting and threshing in Stage 3. Sowing and weeding operations (Stage 2) did not see any significant mechanization in India during this period.

The above evidence shows that while agriculture labor use per hectare has been falling over time, especially for women, farm mechanization has been increasing over time. Next, in Figure 3 we plot the district level agriculture labor use per hectare and the mechanization measure. The figure shows a negative relationship between the two variables, for both men and women. This implies that labor use per hectare is lower in districts where mechanization is higher. The extent of decline in labor usage, however, varies. We observe a much steeper

[19] Table A.2 in Appendix A shows the detailed summary statistics for all soil characteristics controlled in the regression specifications. Table A.3 shows them for all other socio-demographic characteristics used as controls.

decline for male labor use as more machines are used in tilling, in comparison to women.

4.2 Empirical Strategy

The descriptive statistics above suggest that there exists a negative relationship between farm mechanization and labor use per unit cultivated land in India. In order to draw a causal link between farm mechanization and agricultural employment we estimate the below specification using data from 1999 to 2011:

$$L^g_{dst} = \beta^g_0 + \beta^g_1 Mechanization_{dst} + X^g_{dst}\beta^g_2 + X_{dst}\beta^g_3 + D_s + D_t + \epsilon^g_{dst} \tag{6}$$

Here, d refers to district, in state s at time t and the superscript g refers to gender, i.e. either male or female labor. The dependent variable is an inverse hyperbolic sine transformation of labor input used per unit of cultivated land (L).[20] The interpretation of the estimates obtained using the inverse hyperbolic sine transformation is the same as those obtained using a natural logarithm transformation of the dependent variable, with the advantage of being defined at zero (Burbidge *et al.* (1988)). In the above specification, $Mechanization_{dst}$ captures the intensity of machine usage in Stage 1, i.e. $Tilling$. It is defined as the total area tilled by machines divided by the total area cultivated (then multiplied by 100), in district d and year t. Our main coefficient of interest here is β_1 which captures the percentage change in labor use per hectare when intensity of mechanization increases by one percentage point. The 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 & Ramaswami (2017)) and is supported by the literature that shows inter-

[20] We use this transformation to account for the possibility of zero labor usage in some districts. While there are no districts with zero male labor use, around 11 districts report zero female labor use. This problem is more acute in operation level analyses, where some districts may report zero labor use for a particular gender in a given operation. Using IHS transformation helps to maintain the same number of observations across specifications. It also aids in conducting across equation coefficient testing (Chi-square test) which requires same number of observations in both equations. However, we also estimate specification with log dependent variable and find that if anything our main conclusions are strengthened by an increase in coefficient magnitude on the effect of mechanization on female labor use.

district migration rates for employment to be low for India (Munshi & Rosenzweig (2009)).

Gender specific district controls, such as initial labor use per unit of cultivated land (measured in 1993) and education are included in X^g_{dst}. District level controls, viz. depth, slope and pH of the soil, irrigation, crop composition, average landholding size, climate, socio-economic characteristics (e.g. caste and religious composition of the district), lagged fertilizer use and indicators for district infrastructure are captured in X_{dst}. State fixed effects and time fixed effects are denoted by D_s and D_t, respectively. Throughout, the regressions are weighted by district population and the standard errors are clustered at district level.

Machine usage is likely to be endogenous to relative factor prices and other economic characteristics of a district. We, therefore, propose an instrumental variable strategy that exploits the linkage between pre-existing soil texture (loamy vs. clayey) and its effect on tillage requirements as a determinant of adoption of mechanization in Stage 1 of the agriculture production process. In our reduced form analysis, the first stage specification is given as below:

$$Mechanization_{dst} = \pi^g_0 + \pi^g_1 Loaminess_{ds} + X^g_{dst}\pi^g_1 + X_{dst}\pi^g_2 + D_s + D_t + e^g_{dst} \qquad (7)$$

Again, here, d refers to district, in state s at time t and the superscript g refers to gender. The first stage is estimated separately for men and women since some controls like past employment and education are gender specific (X^g_{dst}). The instrumental variable $Loaminess$ is defined as the difference in the loamy and clayey soil shares in district d of state s. 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 soils. 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. Figure 4 plots the district level fraction of loamy-clayey soil texture. It shows significant variation in soil texture within a state across districts which can be exploited for our analysis. The instrumental variable estimates in the second stage should then capture the causal effect of machine uptake on farm labor use.

Instrument validity: The relative loaminess of the soil is a valid instrument if it does not affect labor use directly, but only through the take-up of machines. There may be a concern, however, that differences in soil texture can have direct effects on women's labor use in farming. This could happen due to three channels. One, soil texture could affect soil fertility. We test for difference in outcomes like agricultural yield for rice and wheat (major cereals of India), Monthly Per Capita Expenditure (MPCE) and daily agricultural wage rates which capture variation in agricultural productivity and resultant possible variability in incomes, as relative loaminess increases. We use data on these outcomes prior to 1999 to see if they vary by soil texture before the mechanization push that occurred in the country. 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. We control for state fixed effects and other detailed soil characteristics in these regressions.

Second, loaminess could also directly affect women's labor use if historically women are more disadvantaged in areas requiring more primary tilling, a strength intensive operation. For instance, this could happen if crop suitability systematically varies with loaminess and in turn affects labor use by gender. We check for the ratio of area cultivated under wheat and rice (due to the extant literature documenting gender differences in labor use across these two crops) and again find no significant relationship with loaminess after including other controls (Panel C, Table 3). Nevertheless, we control for crop composition in our empirical specification since it can affect labor use directly through other channels.

Lastly, we directly check if male and female labor use in 1993-94 varied by loaminess (Panel A, Table 3). While, we do not find a significant relationship between loaminess and labor use for either gender before the mechanization push occurred, the direction of the relationship is negative for female labor use. Thus, to allay any concern that our instrumental variable estimates are affected by this, all the regressions control for initial agricultural employment levels in 1993-94 (measured as total labor use in farm per unit land cultivated in 1993-94, for men and women separately) and variation in gender norms through state fixed effects. Initial employment will absorb any effects on labor use driven by differential norms around women's labor force participation across areas having different soil textures. It will also account for any other historical geographic conditions that tilt the production technology in favor of male labor such as ploughing requirement across crops and regions (Alesina *et al.* (2013)). Hence, conditional on social norms around gender-based labor allocation, the degree of loaminess of the soil of a district should impact employment only through the adoption of machinery in agriculture.

As discussed earlier, mechanization can have gender differentiated impacts on labor use through two channels - direct effects and indirect effects. The direct effect of machine uptake in Stage 1 tilling is likely to be greater on male labor since they are relatively more involved in the task of land preparation whereas women are more involved in weeding and harvesting. To the extent that men primarily operate tractors in India (Brandtzaeg (1979)), their importance in land preparation could increase. On the other hand, deeper tilling can reduce weed growth, hence reduced weeding labor requirement can consequently reduce demand for women's labor in these tasks.

5 Results

In general, the process of mechanization is endogenous and likely to be driven by decline in availability of cheap farm labor as off farm employment opportunities grow. As men are more likely to be employed in the rural non-farm sector (Afridi *et al.* (2018)), we are more likely to find a negative association between mechanization and male farm labor use in OLS estimates. As a check, we first show the naive OLS estimates of the effect of mechanization on labor use in agriculture in Table A.4 in the Appendix. We add controls sequentially, starting with agricultural characteristics in column (1) - irrigation, average landholding size, crop composition, climate and population living in urban areas. Column (2) includes demographic controls for caste, religion and gender specific education. Usage of other agricultural inputs such as lagged fertilizers are added in column (3). Finally, variables capturing infrastructure development and economic activity which can influence economic activity through access to roads and nightlight intensity are included in column (4). All specifications include state fixed effects, year fixed effects and gender specific initial farm labor use in 1993-94 for the corresponding gender. Overall, the results do not change, for either female or male labor usage, as we augment the specification. Thus, the OLS results show that an increase in tilling machine uptake in agriculture is associated with lower female and male labor use per unit of land cultivated, but only the latter is significant, as expected.

Given the endogeneity concerns, we instrument tilling mechanization by the difference in loamy and clayey soil shares or 'loaminess' in a district, as discussed previously. 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 (corresponding to column (4) in Table A.4) are included in these specifications.[21] As expected, we find that there has been a larger uptake of mechanized implements for primary and secondary tilling in districts within a state having 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 difference in loamy and clayey soil texture on overall mechanization in Stage 1 tilling. The first stage F-stat (adjusted for

[21]The gendered set of controls correspond to the women's initial labor use and their education. An alternative estimation using male controls, gives similar estimates and has been omitted for brevity but first stage F-stats are provided for each specification in the 2SLS results that follow.

district level clustering), though not very large, is greater than 10 throughout, and highest in column (3).[22]

The second stage estimates are reported in Table 5. The specifications in columns (1)-(4) correspond to the previous discussion. The results in column (4), for the specification that has all the controls, show that an increase in mechanization by one percentage point decreases female labor use per hectare by 0.7%. Since there was an increase in the intensity of mechanized primary and secondary tilling equipment in Indian agriculture from 19 in 1999 to 51 in 2011, this estimate implies an increase of 32 percentage point during this period and a consequent reduction in female labor use in agriculture by over 22%, ceteris paribus. Existing literature has documented a fall in female labor force participation in rural areas during 1999-2011 by approximately 9 percentage point. There are two notable facts regarding this decline. First, much of the observed fall remains unexplained by household supply side factors during 1999-2011 (Afridi *et al.* (2018)). Second, the fall in rural women's LFP is largely accounted by the fall in their agricultural employment of 12 percentage point during this period (this is equal to 30% fall in women's agricultural employment during this period).[23] Thus our analyses here shows that a significant proportion (approximately 73.3%) of the decline in women's rural agricultural employment (22% out of 30%) can be explained by increased adoption of machines in the farm sector during 1999-2011 and a consequent reduction in women's participation in agriculture.

On the other hand, in Panel B of Table 5, we do not discern a significant effect of

[22]A concern with the 2SLS results may be that the first-stage F-stat is not very large, though it is significant and larger than 10. Weak instruments could lead to finite sample distributions that are poorly approximated by the theoretical asymptotic distribution. Such concerns are more valid in an overidentified model. Nevertheless, as a check for just identified models with possibly weak instruments, Angrist & Pischke (2008) and Chernozhukov & Hansen (2008) recommend looking at the reduced-form estimates (regressing each dependent variable on all exogenous variables, including the instruments). The sign and the strength of the coefficients in the reduced-form regression can provide evidence of whether a causal relationship exists. Table A.5 shows the results for this test. The reduced form results also show a significantly negative effect of the difference in loamy and clayey soil shares on female labor use per unit land cultivated while there is no effect on male labor use per hectare. Thus, our main results are robust to weak instrument test for exact identification as well.

[23]The fall in agricultural employment was partly compensated by rise in rural construction employment, hence the total decline in rural women's LFP was approximately 9 percentage point among working age women.

mechanization on male labor use though the sign of the coefficient is negative. The chi-square test of equality of the two coefficients rejects the null that the effect of mechanization is same across female and male labor use at 10% level of significance (column (4)). This shows that female labor use per unit area cultivated fell more than that of male due to an exogenous shift in production technology towards machines in Stage 1. These results are in line with our theoretical proposition.

5.1 Robustness

There may be a concern that trends in female labor use in agriculture are determined by their initial level of labor force participation in a district. To address this issue we account for non-linear time trends in agricultural labor use in a district arising from differences in initial labor use, by gender.[24] The estimates obtained are reported in Table 6, columns (1) and (3) for female and male labor, respectively. The baseline results are robust to the inclusion of district specific non-linear employment trends due to differences in initial labor use, suggesting that our results are not driven by labor force participation trends arising from initial differences across districts. We further include controls for state specific trends (again non-linear), along with the previous set of controls to capture trends in the evolution of agricultural labor use due to state level unobservables. The results reported in columns (2) and (4) of Table 6 are again comparable to those obtained in Table 5.

There may be a concern that crop choice responds to mechanization changes. Therefore, we also look at the robustness of our results to including one year lagged values of crop composition instead of contemporaneous crop composition. The results for the baseline specification are shown in Table A.6. Clearly, The coefficient estimates do not change and the previous results continue to hold. We also estimate the baseline specification for each year separately in our analyses. The effect of mechanization on women's total labor use per unit land cultivated is negative across all three years, and comparable in magnitude,

[24] We interact initial employment with indicator variables for each year, thus taking into account non-linearity in trends.

but statistically significant only for 2011. For men, the coefficient on mechanization is insignificant for each year. Overall, the results are stable across years and pooling the data allows us to estimate the impact of mechanization with greater precision. These results are omitted for brevity.

Additionally, we check the robustness of our claim that the difference in loamy and clayey texture of the soil influences mechanized tilling because the depth of tilling requirement is higher in loamy soil. As discussed earlier, sowing is a relatively precision based task and has not seen a large increase in uptake of mechanized implements. Also, many mechanized sowing machines also allow for tilling of soil. For instance, power operated till-sowing machines are used for both tilling and sowing operations.[25] On the other hand, most harvesters used by Indian farmers are self-propelled and not tractor driven, hence the relative loaminess of the soil should clearly not impact adoption of self-propelled harvesters. If the difference in soil texture affects mechanization through other channels, then we should also find a significant increase in take up of machines in harvesting operations in districts with relatively more loamy soil. To test the validity of our instrument to this mechanism, we assess whether there is any impact of the difference in loamy and clayey soil shares in a district on mechanization in other operations, namely, sowing and harvesting/threshing in Table A.7. In line with our hypothesis, we find no significant effect of loaminess on harvesting machinery use, as indicated by the insignificant coefficient in column (2). But there is a small positive effect on sowing equipment, due to the aforementioned reasons.

6 Discussion

Our results show that mechanization of tilling operation has led to a significantly greater reduction in women's labor use in Indian agriculture. What explains this gendered effect of the change in production technology? To answer this question we delve into labor use in

[25] It is not possible to distinguish between machines that only conduct sowing operation and those that allow for both tilling and sowing in the data.

each operation. The NSS surveys capture employment across operations in agriculture in the weekly schedule which allows us to measure work days by operation - total number of days an individual reports working in a specific operation in the reference week, aggregated across the district and divided by the area under cultivation in the district. Two-stage least squares results for labor use in each agricultural operation are reported in Table 7. We find that the observed overall fall in women's agricultural labor is driven primarily by a significant reduction in their contribution to weeding in Stage 2 of the agricultural production process in Panel A. The results show that a one percentage point increase in the intensity of tilling machinery leads to a reduction in women's labor use in weeding by 0.9%, as shown in column (3) of Panel A of Table 7.

This finding lines up with our claim that since women's and men's labor are imperfect substitutes in agricultural production due to sex-specific specialization of tasks, the adoption of machines in tilling operation displaced women's labor that specializes in weeding. The chi-square tests of equality of the coefficient on mechanization for weeding (column 3) with each operation in Panel A indicates that the decline in female labor is significantly different from the impact on tilling (p=0.031), sowing (p=0.0248 and harvesting (p=0.043). 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 weeding. On the other hand, in Panel B, the coefficient on mechanization for male labor use in weeding is significantly different only from tilling (p=0.061). Moreover, the effect of mechanization on male labor in tilling (column 1, Panel B) is positive relative to weeding (column (3), Panel A), suggesting that male labor is likely complementary to machines in Stage 1 while the direction of the impact of machinery on labor use of women in Stage 1 tilling is negative (Column (1), Panel A).

Could improvements in family income due to the mechanization be driving the reduced usage of women's labor? First, our analysis by operation suggests that income effects, if any, are unlikely to explain the fact that the decline in women's labor is primarily in weeding. Second, of the female labor used in agriculture, the proportion that family and the proportion hired is approximately equal. Family labor, however, forms a larger share of total male labor used (around 65%). Analyses by whether farm labor is hired or is provided by family is shown in Table 8. The results show that there was an insignificant, though negative, effect of mechanization on men's family labor usage (column (2), Panel B). Although women's family labor did decline significantly, the decline is not significantly different from the decline in male family labor use. The coefficient on mechanization for hired female labor is also negative but insignificant overall - suggesting that hired female labor is not substituting family labor of women, as would be expected when farm incomes increase. Instead, hired labor use of women (along with family labor) falls relative to male hired labor use on farms. This is shown by the chi-square test for equality of the marginal effects of mechanization on hired female and male labor use (Table 8, column (3), p=0.057). Moreover, in line with the existing literature we find positive but mostly insignificant increases in yields and cropping intensity, weakening any potentially large income effects due to mechanization that could be driving our findings in Table 5.[26]

Third, recall our analysis in Table 7 shows that the overall decline in women's labor is driven by a fall in labor usage for weeding. 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 women's labor use, for both family and hired female labor. The significant decline in women's family labor is observed only in weeding in Table A.8 - this is unlikely to be driven by income effects alone. We also do not observe a substitution of hired labor for family labor or a positive coefficient on hired female labor for weeding which is likely if a rise in household incomes leading to withdrawal of women from own farms is an explanation for our findings. In fact, hired female labor use in weeding also shows a significant fall due to mechanization, reflecting a change in demand structure. Moreover, if increase in household income was the only mechanism at

[26]The impact of tilling machinery uptake on crop yields for major food grains is reported in columns (1)-(3) of Table A.9. The effect on yields is positive, albeit marginally significant only for wheat. 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 an insignificant effect.

play, we should have observed a reduction in women's labor use across all operations.

Furthermore, we also examine the impact of mechanization on the total labor use in agriculture. If farmers are able to undertake multiple cropping due to increased timeliness of operations after machine uptake or if crop productivity increases due to mechanization, then the effect on total labor use due to mechanization is ambiguous. For instance, if crop productivity increases, it could reallocate labor towards harvesting in Stage 3 from Stages 1 and 2 without any change in overall labor use. Table 9 shows the impact of mechanization on the total number of males or females engaged in farm cultivation. Interestingly, increased machine uptake increased total male labor by 0.8% (column (2)) but total female labor fell by 3% (column (1)) for every percentage point increase in mechanization. This suggests that reallocation of women laborers across operations due to any improvements in crop productivity cannot explain the observed decline in female labor use in weeding.[27]

A pertinent question is whether there are any implications of the observed impact of labor use on gender differences in agricultural wage earnings. Unfortunately the NSS records wages only for hired farm labor. This may not reflect the overall impact on wage rates or labor productivity since family labor constitutes a significant proportion of the total farm labor. Nevertheless, in Table A.10, column (1) we report the impact of mechanization on female (Panel A) and male (Panel B) wage rates. Farm daily wage rates increased for both men and women by around 0.6% for a 1 percentage point increase in mechanization. Thus, adoption of machinery can reduce labor use, but increase wage rate through a positive impact on hired labor productivity, a possibility captured in our theoretical model as well under a certain parametric space. Column (2) shows the impact on female (Panel A) and male earnings (Panel B), accounting for the intensity of work or the number of workdays in a week. The rise in wage rates (column 1) led to a significant increase in male earnings by 3.5% but for women there was no significant change in wage earnings due to the decline in their labor use (or intensity of work) as shown in our previous analysis. The difference in earnings impact is

[27] The results in Table 9 for total labor are also held up by our theoretical model. The parametric space under which these results are feasible are available on request.

only marginally significant at 15% level (p=0.125). This provides suggestive evidence that the observed fall in labor use of women may have exacerbated extant gender differences in wage earnings.[28] Technological change can, thereby, influence income inequality between men and women.

Lastly, if women are pushed away from agriculture due to mechanization, are they able to find alternative employment in other sectors? To test for this we examine whether changes in employment in manufacturing, construction and service sectors for both men and women in rural areas during 1999-2011 are related to agricultural mechanization using the instrumental variable strategy. The results are reported in Table 10 and show no effect of agricultural mechanization on employment in these sectors in rural areas (Columns (1), (2) and (3)) for women in Panel A. Thus, we find no evidence for women gaining employment in other sectors in these areas, a feature that is generally consistent with the declining female labor force participation in India (Afridi *et al.* (2018)). Furthermore, there is no impact of agricultural mechanization on either male employment or overall employment including urban areas (Columns (4), (5) and (6)), suggesting that trends in employment and in the labor market, in general, are not driving our results.

7 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 adoption of tractors for tilling the land, we find that a one percentage point increase in mechanization decreases female labor use per hectare by 0.7%. 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 estimate implies a reduction in female labor use

[28] On average, male daily wage rates are 30% higher than female wage rate in agriculture in India (Authors' own calculations, National Sample Survey Rounds).

in agriculture by over 22%, ceteris paribus, during the period of our study.

Our results extend the broader literature on the effects of technological change on labor. The findings suggest that in contexts where there exists division of labor due to innate or biological factors, technological change may adversely affect one type of labor 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 find 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 technological change.

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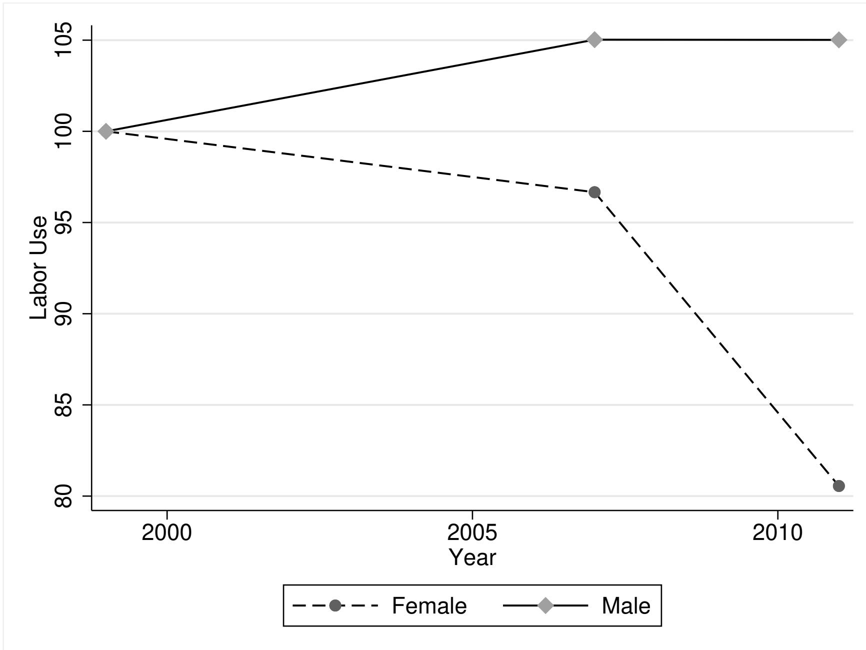
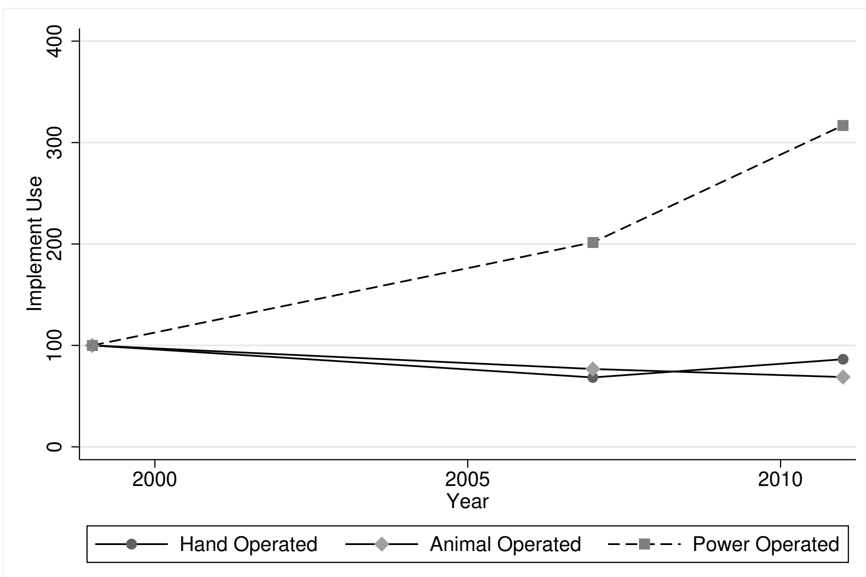
Figure 1: Trends in Labor and Implement Use in Indian Agriculture



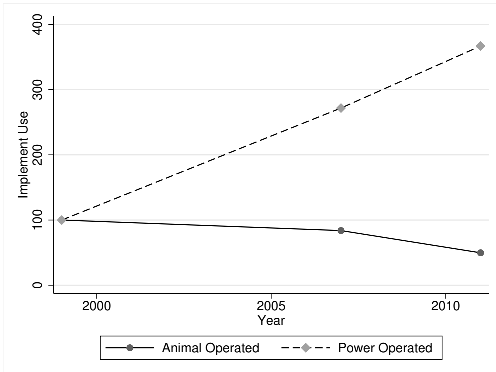
(a) Labor Use (by gender)



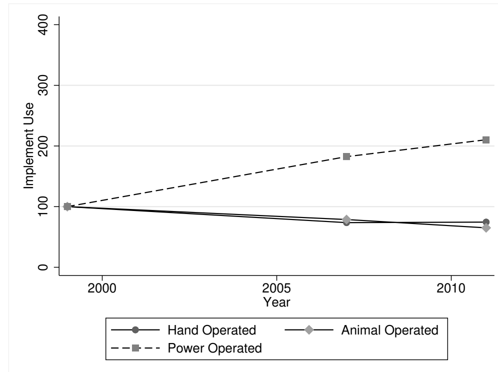
(b) Implement Use (by source of power)

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.

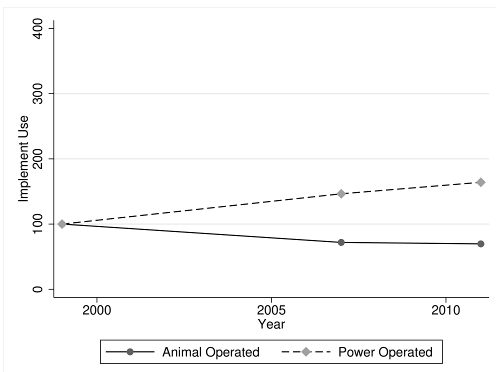
Figure 2: Implement Usage: Sources of Power by Agricultural Operations



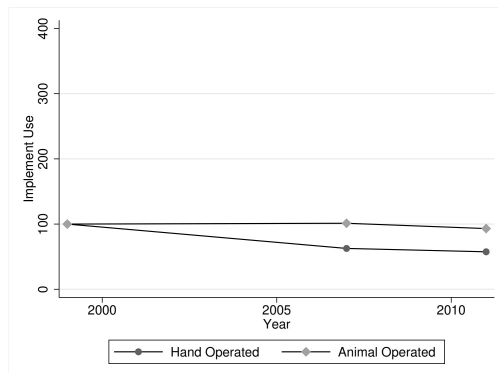
(a) Stage 1: Primary Tilling



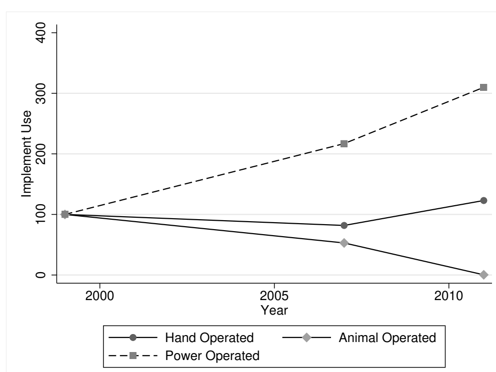
(b) Stage 1: Secondary Tilling



(c) Stage 2: Sowing



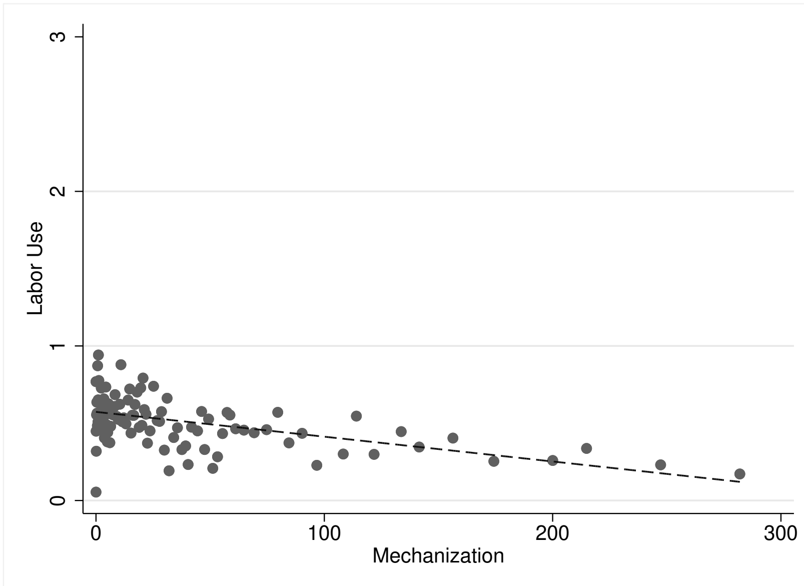
(d) Stage 2: Weeding



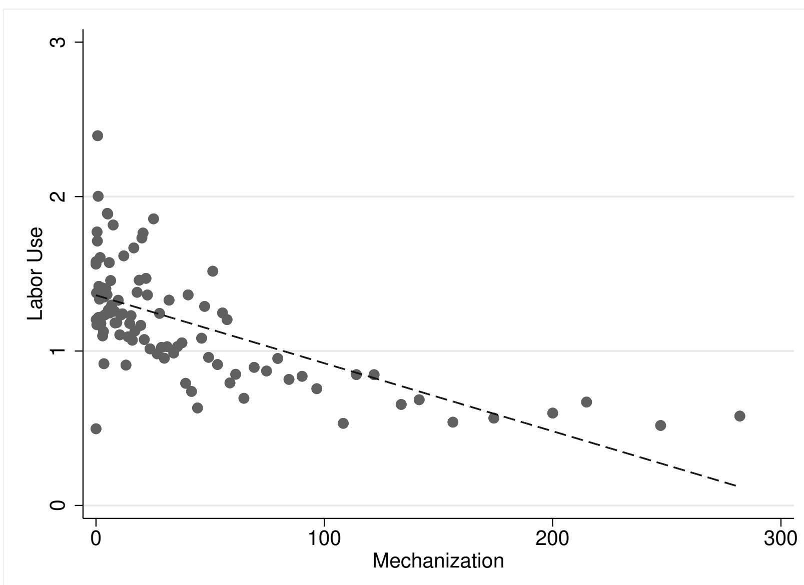
(e) Stage 3: Harvesting & Threshing

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.

Figure 3: Mechanization and Farm Labor Use



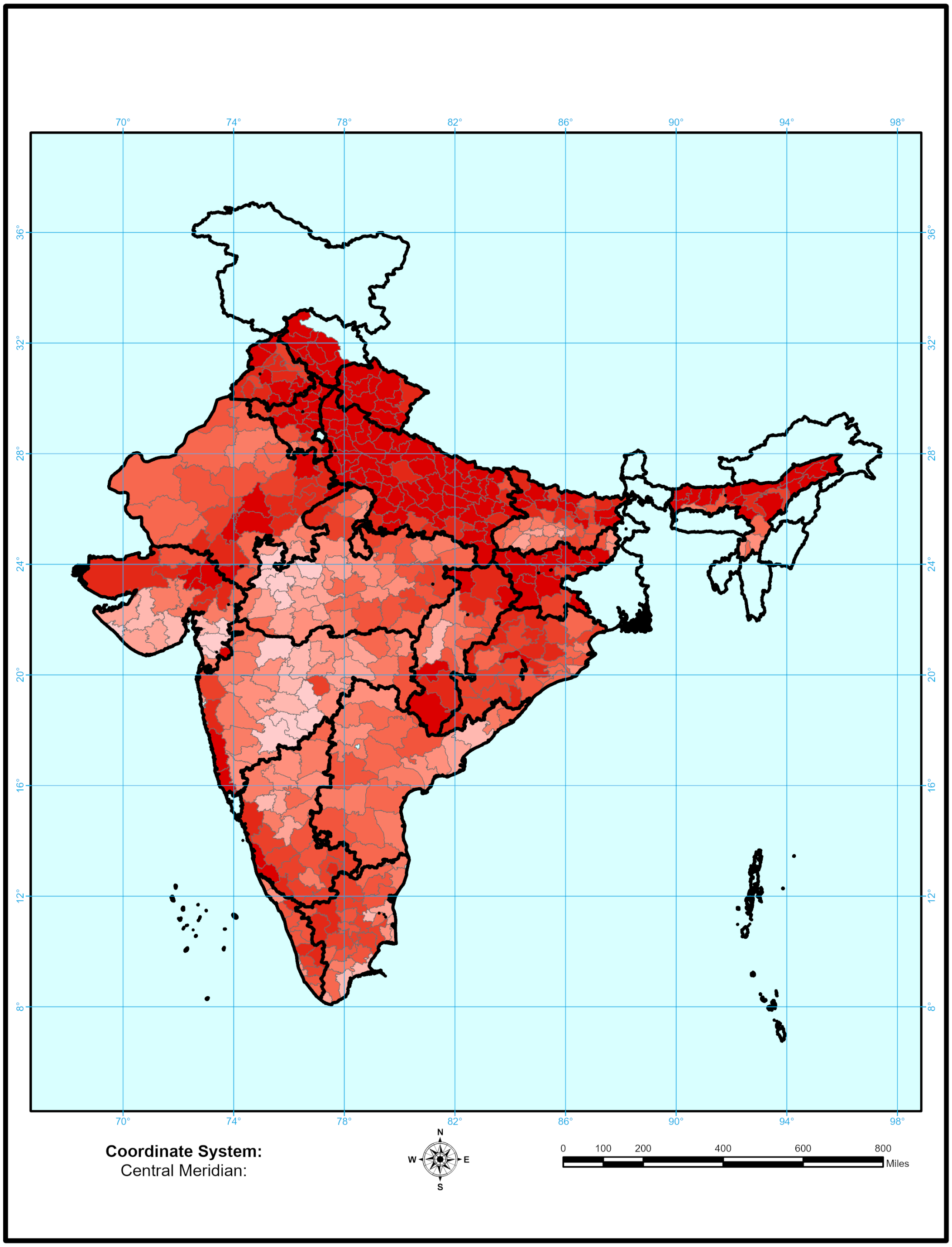
(a) Female Labor



(b) Male Labor

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. 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 4: 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 1: 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/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 machines and area cultivated. Authors' own calculations.
Note: Workers employed in farm sector as their usual status activity are included in labor use. Mechanization is defined as the area under primary and secondary tilling power operated machines divided by the total area cultivated in the district.

Table 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 :			
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
Climate:			
Rainfall	Total yearly precipitation (mm)	1204	684
Temperature	Mean yearly temperature (^oC)	25.6	1.55
Miscellaneous:			
Urban population	Proportion of urban population	0.235	0.154
Average land-size	Average size of landholding (ha)	1.38	1.15
Irrigated Area	Proportion of sown area under irrigation	0.497	0.289
Lagged Agricultural 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
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

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 the three years are shown for brevity.

Table 3: Agricultural yields, Wages, Labor Use, Cropping Patterns and their relation to Loaminess: Pre-mechanization period

(1)	(2) Loaminess	(3) Observations	(4) R-Squared
	Panel A: Labor use per hectare		
Male labor per hectare	0.01	411	0.63
	(0.042)		
Female labor per hectare	-0.048	411	0.45
	(0.043)		
	Panel B: Wage rate and income		
Wage Rate - Female	-0.02	363	0.5
	(0.044)		
Wage Rate - Male	-0.054	397	0.58
	(0.034)		
MPCE	-0.0031	411	0.47
	(0.026)		
	Panel C: Cropping pattern and yields		
Ratio of Cropped area : Wheat by Rice	-10.25	388	0.21
	(5.581)		
Wheat Yield	0.052	330	0.79
	(0.054)		
Rice Yield	0.048	388	0.73
	(0.061)		

Source: Labor use per hectare, 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 District-wise Crop Production Statistics published by Ministry of Agriculture (year 1998).
Note: Each row shows the coefficient estimate on loaminess i.e. the difference in loamy and clayey soil texture in a district, when the variable mentioned in Column (1) is regressed on loaminess, state fixed effects and other soil characteristics like ph, slope and depth of the soil. Male and female labor per hectare are defined in the same way as in equation 6. We take of log of daily agricultural wage rate, MPCE, wheat and rice yields. Ratio of cropped area is in levels. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of Difference in Loamy and Clayey Soil Shares on Mechanization (First Stage)

	(1)	(2)	(3)
	Primary Tilling	Secondary Tilling	Mechanization (Total)
Loaminess	6.363***	5.773***	12.14***
	(1.939)	(1.770)	(3.373)
Constant	29.51	-29.29	0.219
	(44.05)	(40.32)	(77.53)
F-Stat	10.76	10.64	12.94
N	1073	1073	1073
Controls			
Agriculture	✓	✓	✓
Demographic	✓	✓	✓
Development	✓	✓	✓
Lagged Agri Input	✓	✓	✓

Note: 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. 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. 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. All specifications control for initial labor use in agriculture (female), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education (female). Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1)	(2)	(3)	(4)
Panel A: Female labor per hectare				
Mechanization	-0.007*	-0.008**	-0.008**	-0.007**
	(0.004)	(0.004)	(0.004)	(0.003)
Constant	0.357	0.385	0.816	1.412
	(0.940)	(1.072)	(1.074)	(0.886)
Observations	1077	1077	1077	1073
FS F-Stat	7.744	9.728	9.471	12.941
Panel B: Male labor per hectare				
Mechanization	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
Constant	0.491	0.669	0.729	0.797
	(0.891)	(0.949)	(0.961)	(0.813)
Observations	1077	1077	1077	1073
FS F-Stat	7.890	9.486	9.262	12.950
Test of Equality[p-value] Female-Male	0.113	0.068	0.090	0.079
Controls				
Agriculture	✓	✓	✓	✓
Demographic		✓	✓	✓
Development			✓	✓
Lagged Agri Input				✓

Note: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land 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. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Column (1)-(4) add controls sequentially. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1)	(2)	(3)	(4)
	Female labor per hectare		*Male labor per hectare*	
Mechanization	-0.006**	-0.005**	-0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.002)
Constant	1.311	1.174	0.833	0.969
	(0.859)	(0.771)	(0.798)	(0.794)
Observations	1073	1073	1073	1073
FS F-Stat	13.12	17.56	13.37	18.41
Controls				
Agriculture	✓	✓	✓	✓
Demographic	✓	✓	✓	✓
Development	✓	✓	✓	✓
Lagged Agri Input	✓	✓	✓	✓
Additional Controls				
Initial District Employment × Time	✓	✓	✓	✓
State × Time		✓		✓

Note: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land 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. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: 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				
Mechanization	-0.000	-0.001	-0.009**	0.001
	(0.001)	(0.002)	(0.004)	(0.003)
Constant	0.307*	-0.402	0.155	2.168**
	(0.173)	(0.549)	(1.222)	(1.013)
Observations	1073	1073	1073	1073
FS F-Stat	12.941	12.941	12.941	12.941
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.031	0.048	.	0.043
Panel B: Male labor per hectare				
Mechanization	0.006	0.003	-0.005	-0.004
	(0.004)	(0.003)	(0.005)	(0.004)
Constant	0.193	0.189	-0.085	2.720*
	(1.065)	(0.830)	(1.145)	(1.451)
Observations	1073	1073	1073	1073
FS F-Stat	12.950	12.950	12.950	12.950
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.061	0.178	.	0.789
Controls				
Agriculture	✓	✓	✓	✓
Demographic	✓	✓	✓	✓
Development	✓	✓	✓	✓
Lagged Agri Input	✓	✓	✓	✓

Note: 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. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

	(1)	(2)	(3)
	Overall	Family	Hired
Panel A: Female labor per hectare			
Mechanization	-0.007**	-0.005**	-0.001
	(0.003)	(0.003)	(0.001)
Constant	1.412	1.272**	0.143
	(0.886)	(0.625)	(0.500)
Observations	1073	1073	1073
FS F-Stat	12.941	12.941	12.941
Test of Equality [p-value]			
Col.(2)=Col.(3)		[0.087]	
Panel B: Male labor per hectare			
Mechanization	-0.001	-0.004	0.004
	(0.002)	(0.003)	(0.003)
Constant	0.797	0.567	0.497
	(0.813)	(0.742)	(0.642)
Observations	1073	1073	1073
FS F-Stat	12.950	12.950	12.950
Test of Equality [p-value]			
Col.(2)=Col.(3)		[0.050]	
Test of Equality [p-value]			
Female=Male	0.079	0.453	0.057
Controls			
Agriculture	✓	✓	✓
Demographic	✓	✓	✓
Development	✓	✓	✓
Lagged Agri Input	✓	✓	✓

Note: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land 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. All specification control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of Mechanization on Total Farm Labor (2SLS)

	(1)	(2)
	Female Labor	*Male Labor*
Mechanization	-0.030*	0.008*
	(0.016)	(0.004)
Constant	15.994***	13.151***
	(4.395)	(1.221)
Observations	1073	1073
FS F-Stat	14.157	13.527
Test of Equality [p-value]		
Female=Male	[0.025]	
Controls		
Agriculture	✓	✓
Demographic	✓	✓
Development	✓	✓
Lagged Agri Input	✓	✓

Note: 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. All specifications control for total initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of Mechanization on Non-Agricultural Labor (2SLS)

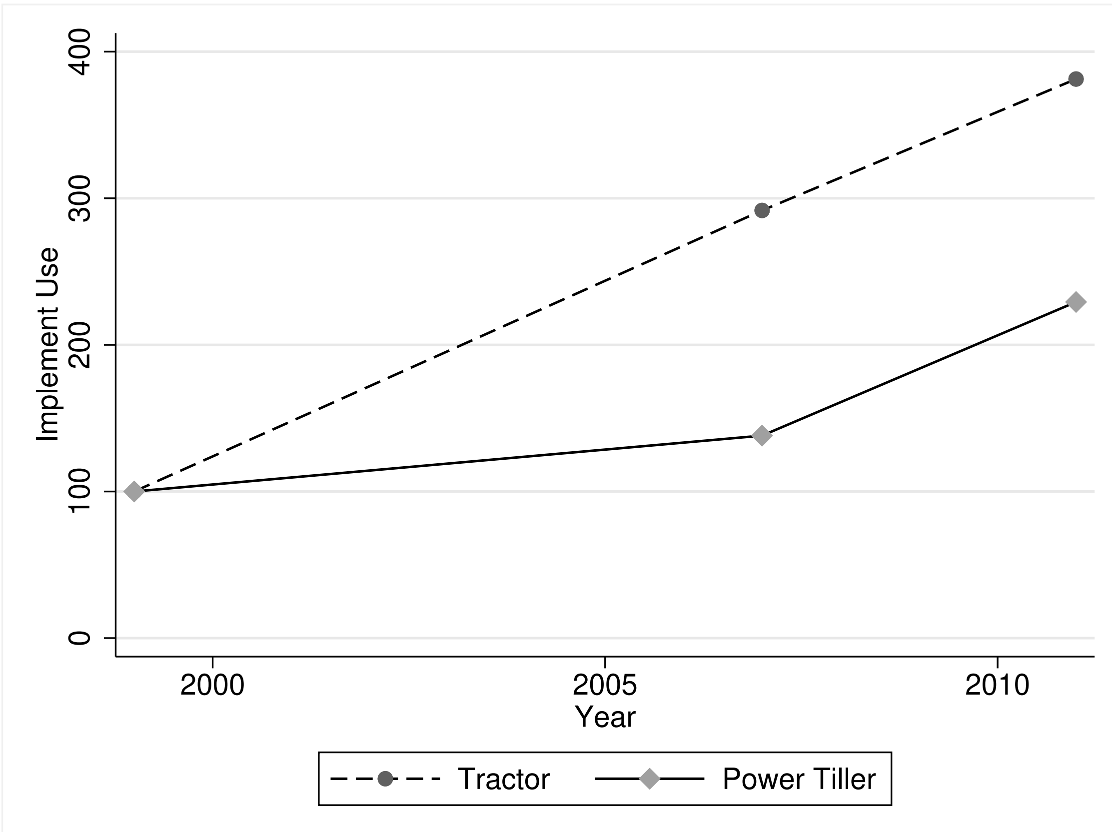
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Labor						
	Rural			*Rural & Urban*		
	Manu	Cons	Serv	Manu	Cons	Serv
Mechanization	0.000	0.000	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.762	-0.790***	-0.006	0.715	-0.790***	-0.299
	(0.564)	(0.230)	(0.222)	(0.600)	(0.214)	(0.273)
Observations	1073	1073	1073	1073	1073	1073
FS F-Stat	12.941	12.941	12.941	12.941	12.941	12.941
Panel B: Male Labor						
	Rural			*Rural & Urban*		
	Manu	Cons	Serv	Manu	Cons	Serv
Mechanization	-0.000	0.001	-0.000	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.313	-0.127	0.050	0.106	-0.148	-0.029
	(0.207)	(0.257)	(0.157)	(0.231)	(0.197)	(0.183)
Observations	1073	1073	1073	1073	1073	1073
FS F-Stat	12.950	12.950	12.950	12.950	12.950	12.950
Controls						
Agriculture	✓	✓	✓	✓	✓	✓
Demographic	✓	✓	✓	✓	✓	✓
Development	✓	✓	✓	✓	✓	✓
Lagged Agri Input	✓	✓	✓	✓	✓	✓

Note: The dependent variable is an inverse hyperbolic sine transformation of proportion of female/male aged 15-65 working in manufacturing (columns 1 and 4), construction (columns 2 and 5) and services (columns 3 and 6) 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. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

A Additional Analysis

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.

Table A.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 A.2: 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).

Table A.3: 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.4: Effect of Mechanization on Farm Labor Use: OLS Estimates

	(1)	(2)	(3)	(4)
Panel A: Female labor per hectare				
Mechanization	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.632	0.818	1.062	1.265*
	(0.700)	(0.700)	(0.705)	(0.672)
Observations	1077	1077	1077	1073
R-squared	0.524	0.538	0.545	0.557
Panel B: Male labor per hectare				
Mechanization	-0.000**	-0.000**	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.499	0.708	0.770	0.796
	(0.897)	(0.946)	(0.959)	(0.840)
Observations	1077	1077	1077	1073
R-squared	0.712	0.721	0.724	0.749
Controls				
Agriculture	✓	✓	✓	✓
Demographic		✓	✓	✓
Development			✓	✓
Lagged Agri Input				✓

Note: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land 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. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Column (1)-(4) add controls sequentially. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Effect of Difference in Loamy and Clayey Soil Shares on Farm Labor Use: Reduced Form

	(1)	(2)
	Female labor per hectare	*Male labor per hectare*
Loaminess	-0.079**	-0.009
	(0.032)	(0.027)
Constant	1.410**	0.810
	(0.684)	(0.837)
Observations	1073	1073
R-squared	0.561	0.746
Controls		
Agriculture	✓	✓
Demographic	✓	✓
Development	✓	✓
Lagged Agri Input	✓	✓

Note: The dependent variable is an inverse hyperbolic sine transformation of total labor use per hectare land cultivated in a district. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, ph and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Effect of Mechanization on Farm Labor Use (2SLS) - Robustness (Lagged Crop Composition)

	(1)	(2)
	Female labor per hectare	*Male labor per hectare*
Mechanization	-0.007**	-0.001
	(0.004)	(0.003)
Constant	1.347	0.316
	(0.884)	(0.732)
Observations	1073	1073
FS F-Stat	10.06	10.06
Test of Equality[p-value] Female-Male	[0.095]	
Controls		
Agriculture	✓	✓
Demographic	✓	✓
Development	✓	✓
Lagged Agri Input	✓	✓

Note: The dependent variable is an inverse hyperbolic sine transformation of labor use per hectare cultivated land 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. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size,lagged crop composition (preceding year), climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. F-Stat may vary slightly 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effect of Difference in Loamy and Clayey Soil Shares on Usage of Other Power Operated Implements

	(1)	(2)
	Sowing	Harvesting
Loaminess	2.228*	-1.023
	(1.264)	(1.819)
Constant	-14.894	6.451
	(27.345)	(39.415)
Observations	1073	1073
R-squared	0.675	0.554
Controls		
Agriculture	✓	✓
Demographic	✓	✓
Development	✓	✓
Lagged Agri Input	✓	✓

Note: The dependent variable in column (1) is the area operated under sowing power operated machines divided by the total area cultivated in a district. 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. 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 controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education (female). Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Effect of Mechanization on Farm Labor Use by Type and Agricultural Operation (2SLS)

	(1)	(2)	(3)	(4)
	Tilling	Sowing	Weeding	Harvesting
Panel A: Female labor per hectare				
Family Labor	-0.000	-0.001	-0.005**	-0.001
	(0.001)	(0.001)	(0.003)	(0.003)
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.054	0.099	.	0.134
Hired Labor	-0.000	0.000	-0.004*	0.001
	(0.000)	(0.001)	(0.002)	(0.002)
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.077	0.078	.	0.063
Panel B: Male labor per hectare				
Family Labor	0.001	0.001	-0.005	-0.004
	(0.003)	(0.003)	(0.004)	(0.004)
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.189	0.256	.	0.798
Hired Labor	0.007**	0.004	-0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.004)
Test of Equality [p-value] Col(3)=Col(1)/(2)/(4)	0.037	0.133	.	0.429
Observations	1073	1073	1073	1073
Controls				
Agriculture	✓	✓	✓	✓
Demographic	✓	✓	✓	✓
Development	✓	✓	✓	✓
Lagged Agri Input	✓	✓	✓	✓

Note: 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. Mechanization is defined as the area operated under primary and secondary tilling power operated machines divided by the total area cultivated in a district. All specifications control for initial labor use in agriculture (by gender), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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.).* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effect of Mechanization on Yield and Cropping Intensity (2SLS)

	(1)	(2)	(3)	(4)
	Yield			*Cropping Intensity*
	Rice	Wheat	Coarse Cereals	
Mechanization	0.001	0.010*	0.006	0.058
	(0.004)	(0.006)	(0.004)	(0.303)
Constant	0.174	6.630	1.568	100.748**
	(0.891)	(4.698)	(2.025)	(50.553)
Observations	980	803	956	1073
FS F-Stat	12.01	3.26	12.22	14.20
Controls				
Agriculture	✓	✓	✓	✓
Demographic	✓	✓	✓	✓
Development	✓	✓	✓	✓
Lagged Agri Input	✓	✓	✓	✓

Note: 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, state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. Regressions weighted by district population. Robust standard errors clustered at the district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Effect of Mechanization on Wage Rate and Earnings (2SLS)

	(1)	(2)
	Wage Rate	*Wage Earnings*
Panel A: Females		
Mechanization	0.006*	0.010
	(0.003)	(0.010)
Observations	804	804
FS F Stat	9.156	7.093
Panel B: Males		
Mechanization	0.005*	0.035**
	(0.003)	(0.015)
Observations	969	969
FS F-Stat	10.448	10.248
Test of Equality [p-value]		
Female=Male	[0.720]	[0.125]
Controls		
Agriculture	✓	✓
Demographic	✓	✓
Development	✓	✓
Lagged Agri Input	✓	✓

Note: 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. 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), state fixed effects and year fixed effects. Agriculture controls include depth, pH and slope of the soil, irrigation, landholding size, crop composition, climate and fraction of urban population. Demographic controls include caste, religion, education. Lagged agricultural inputs include fertilizer consumption in the preceding year. Development controls include access to roads and night light luminosity. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Theoretical model - Proof of Proposition

Partially differentiating the composite labor expression (2) with respect to F_a and M_a gives us,

$$\frac{\partial L_a}{\partial F_a} = \alpha(F_a)^{(\frac{-1}{\epsilon})}[\alpha(F_a)^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha)(M_a)^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{1}{(\epsilon-1)}},$$

$$\frac{\partial L_a}{\partial M_a} = (1-\alpha)(M_a)^{(\frac{-1}{\epsilon})}[\alpha(F_a)^{\frac{(\epsilon-1)}{\epsilon}} + (1-\alpha)(M_a)^{\frac{(\epsilon-1)}{\epsilon}}]^{\frac{1}{(\epsilon-1)}}$$

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

$$\frac{\partial Y_a}{\partial F_a} = \frac{\partial Y_a}{\partial L_a}\frac{\partial L_a}{\partial F_a}, \quad and, \quad \frac{\partial Y_a}{\partial M_a} = \frac{\partial Y_a}{\partial L_a}\frac{\partial L_a}{\partial M_a},$$

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

$$\frac{w_m}{w_f} = \frac{\frac{\partial L_a}{\partial M_a}}{\frac{\partial L_a}{\partial F_a}},$$

which ensures that

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

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

$$L_a = F_a\frac{1}{\alpha^{\epsilon}(w_m)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}} = M_a\frac{1}{(1-\alpha)^{\epsilon}(w_f)^{\epsilon}}\left[\Delta\right]^{\frac{\epsilon}{(\epsilon-1)}}$$

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 $\Theta \equiv [\theta(A_L L_a)^{\frac{(\sigma-1)}{\sigma}} + (1-\theta)(A_K T_a)^{\frac{(\sigma-1)}{\sigma}}]$ so that we can write $L_a = F_a\delta = M_a\Omega$ and $Y_a = A_a\left[\Theta\right]^{\frac{\sigma}{(\sigma-1)}}$.
It can be verified that differentiating the final output Y_a with respect to M_a and T_a and some simplifications thereafter can give us

$$\frac{\partial Y_a}{\partial M_a} = A_a(\theta)A_L^{'}\left[\theta + (1-\theta)\left(\frac{A_K T_a}{A_L^{'}M_a}\right)^{\frac{(\sigma-1)}{\sigma}}\right]^{\frac{1}{(\sigma-1)}},$$

$$\frac{\partial Y_a}{\partial T_a} = A_a(1-\theta)A_K\left[(1-\theta) + \theta\left(\frac{A_L^{'}M_a}{A_K T_a}\right)^{\frac{(\sigma-1)}{\sigma}}\right]^{\frac{1}{(\sigma-1)}}$$

respectively, where $A_L^{'} \equiv A_L\Omega$. Now, using this expression in the equilibrium condition for male labor, namely equation (4), we derive the following equilibrium male labor use

$$M_a = \frac{A_K T_a}{A_L^{'}}\left[\frac{1}{1-\theta}\left[\frac{P_a A_a(\theta)A_L^{'}}{w_m}\right]^{(1-\sigma)} - \frac{\theta}{1-\theta}\right]^{\frac{\sigma}{1-\sigma}}.$$

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

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

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

$$F_a = \frac{A_K T_a}{A_L''} \left[\frac{1}{1-\theta} \left[\frac{P_a A_a(\theta) A_L''}{w_f} \right]^{(1-\sigma)} - \frac{\theta}{1-\theta} \right]^{\frac{\sigma}{1-\sigma}}$$

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

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

Repeating the exercise for the factor land gives us the following

$$T_a = \frac{A_L' M_a}{A_K} \left[\frac{1}{\theta} \left[\frac{P_a A_a(1-\theta) A_K}{r} \right]^{(1-\sigma)} - \frac{1-\theta}{\theta} \right]^{\frac{\sigma}{1-\sigma}}$$

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

$$T_a = \frac{A_L'' F_a}{A_K} \left[\frac{1}{\theta} \left[\frac{P_a A_a(1-\theta) A_K}{r} \right]^{(1-\sigma)} - \frac{1-\theta}{\theta} \right]^{\frac{\sigma}{1-\sigma}}.$$

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

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

It can be verified that

$$\frac{\partial \odot}{\partial A_a} = \left[\frac{1}{1-\theta} \left[\frac{P_a(\theta) A_L'}{w_m} \right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma} \right], \tag{B.8}$$

$$\frac{\partial \otimes}{\partial A_a} = \left[\frac{1}{1-\theta} \left[\frac{P_a(\theta) A_L''}{w_f} \right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma} \right], \tag{B.9}$$

and finally,

$$\frac{\partial \tau}{\partial A_a} = \left[\frac{1}{\theta} \left[\frac{P_a(1-\theta) A_K}{r} \right]^{(1-\sigma)} (1-\sigma)(A_a)^{-\sigma} \right]. \tag{B.10}$$

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

$$\frac{\partial M_a}{\partial A_a} = \frac{A_K}{A_L'} \frac{\partial T_a}{\partial A_a} [\odot]^{\frac{\sigma}{1-\sigma}} + \frac{A_K T_a}{A_L'} \left(\frac{\sigma}{1-\sigma} \right) [\odot]^{\frac{2\sigma-1}{1-\sigma}} \frac{\partial \odot}{\partial A_a}, \tag{B.11}$$

$$\frac{\partial F_a}{\partial A_a} = \frac{A_K}{A_L''} \frac{\partial T_a}{\partial A_a} [\otimes]^{\frac{\sigma}{1-\sigma}} + \frac{A_K T_a}{A_L''} \left(\frac{\sigma}{1-\sigma} \right) [\otimes]^{\frac{2\sigma-1}{1-\sigma}} \frac{\partial \otimes}{\partial A_a} \tag{B.12}$$

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

$$\frac{\partial T_a}{\partial A_a} = \frac{A_L'}{A_K} \frac{\partial M_a}{\partial A_a} [\tau]^{\frac{\sigma}{1-\sigma}} + \frac{A_L' M_a}{A_K} \left(\frac{\sigma}{1-\sigma} \right) [\tau]^{\frac{2\sigma-1}{1-\sigma}} \frac{\partial \tau}{\partial A_a}, \tag{B.13}$$

or alternatively,

$$\frac{\partial T_a}{\partial A_a} = \frac{A_L^{''}}{A_K}\frac{\partial F_a}{\partial A_a}\left[\tau\right]^{\frac{\sigma}{1-\sigma}} + \frac{A_L^{''}F_a}{A_K}\left(\frac{\sigma}{1-\sigma}\right)\left[\tau\right]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial \tau}{\partial A_a}. \tag{B.14}$$

Using equations B.8 and B.13, equation B.11 can finally be written as follows

$$\frac{\partial M_a}{\partial A_a} = \frac{M_a\left[\left[\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_a(1-\theta)A_K}{r}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\odot\right]^{\frac{\sigma}{1-\sigma}}\right] + \left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_a(\theta)A_L^{'}}{w_m}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]\right]}{\left[1-\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\odot\right]^{\frac{\sigma}{1-\sigma}}\right]}. \tag{B.15}$$

Similarly, for female labor use, using equations B.9 and B.13, equation B.12 we can show that

$$\frac{\partial F_a}{\partial A_a} = F_a\frac{\left[\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_a(1-\theta)A_K}{r}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]\left[\otimes\right]^{\frac{\sigma}{1-\sigma}}\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\right] + \left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_a(\theta)A_L^{''}}{w_f}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]}{\left[1-\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\otimes\right]^{\frac{\sigma}{1-\sigma}}\right]}. \tag{B.16}$$

Proof of part (a):
Note that

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

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

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Leftrightarrow \left[\left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_a(\theta)A_L^{''}}{w_f}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right] < \left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_aA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right].$$

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

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Leftrightarrow \left[(\theta)^{\sigma}\left(\frac{w_f}{A_L^{''}}\right)^{(1-\sigma)}\right] - \left[(1-\theta)^{\sigma}\left(\frac{r}{A_K}\right)^{(1-\sigma)}\right] < 0. \tag{B.17}$$

It is straightforward from above that

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Leftrightarrow \left(\frac{\theta}{1-\theta}\right)^{\sigma}\left(\frac{w_fA_K}{A_Lr}\right)^{(1-\sigma)} < (\delta)^{(1-\sigma)},$$

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

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Leftrightarrow \delta > \left(\frac{\theta}{1-\theta}\right)^{\frac{\sigma}{1-\sigma}}\left(\frac{w_fA_K}{A_Lr}\right) \equiv N.$$

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 $N = \left[\frac{w_f}{w_m} \cdot M\right]$ where we assume that

$$M \equiv \left(\frac{\theta}{1-\theta}\right)^{\left(\frac{\sigma}{1-\sigma}\right)} \left(\frac{w_m A_K}{r A_L}\right) > 1. \tag{B.18}$$

This implies that

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Rightarrow \left(\frac{1-\alpha}{\alpha}\right)^{(\epsilon-1)} \left(\frac{w_f}{w_m}\right)^{(\epsilon-1)} > \frac{\left[\frac{w_f}{w_m} \cdot M\right]^{\left(\frac{\epsilon-1}{\epsilon}\right)}}{1-\alpha} - \left(\frac{\alpha}{1-\alpha}\right). \tag{B.19}$$

If we make the following assumption

$$(1-\alpha) < \left[\frac{w_f}{w_m} \cdot M\right]^{\left(\frac{\epsilon-1}{\epsilon}\right)}, \tag{B.20}$$

taking log on both the sides we get the following

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

If the following restriction

$$\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right] < 1, \tag{B.21}$$

holds, we get

$$\epsilon < \frac{\log\left[\frac{w_f}{w_m} \cdot M\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right]}. \tag{B.22}$$

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

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

which is equivalent to $\alpha > 0$. Since, $\alpha > 0$ is assumed in our setup in the very beginning, we can argue that $\frac{\log\left[\frac{w_f}{w_m} \cdot M\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right]} > 1$. If B.22 holds, we can substitute B.20 in B.19 which finally gives us the following

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

Taking log on both the sides we get the following,

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

Further, if we have

$$\log\left(\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right) > 0, \tag{B.23}$$

we can show that

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

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

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

we can assert that,

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

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

$$\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \min\left[\frac{\log\left[\frac{w_f}{w_m}\cdot M\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{M}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha}\cdot\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right]\right). \tag{B.24}$$

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

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

which implies

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

Further, given

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

we have

$$\frac{\partial\odot^{\frac{\sigma}{1-\sigma}}}{\partial A_a} = \left(\frac{\sigma}{1-\sigma}\right)[\odot]^{\frac{2\sigma-1}{1-\sigma}}\frac{\partial\odot}{\partial A_a} = [\odot]^{\frac{2\sigma-1}{1-\sigma}}\left[\frac{\sigma}{1-\theta}\left[\frac{P_aA_L'(\theta)}{w_m}\right]^{(1-\sigma)}A_a^{-\sigma}\right]. \tag{B.25}$$

Using the expressions for M_a we have the following

$$\frac{\partial\left(\frac{A_L'M_a}{A_K}\right)}{\partial A_a} = \frac{\partial T_a}{\partial A_a}[\odot]^{\frac{\sigma}{1-\sigma}} + T_a\left[\frac{\partial[\odot]^{\frac{\sigma}{1-\sigma}}}{\partial A_a}\right] \tag{B.26}$$

and from the expression for T_a, we get

$$\frac{\partial T_a}{\partial A_a}=\frac{\partial\left(\frac{A_L^{'}M_a}{A_K}\right)}{\partial A_a}\left[\tau\right]^{\frac{\sigma}{1-\sigma}}+\left(\frac{A_L^{'}M_a}{A_K}\right)\frac{\partial\tau^{\frac{\sigma}{1-\sigma}}}{\partial A_a}. \tag{B.27}$$

Now, substituting B.25 and B.26 in B.27 and some further simplification guarantees that

$$\frac{\partial T_a}{\partial A_a}=T_a\frac{\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_aA_L^{'}(\theta)}{w_m}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\odot\right]^{\frac{\sigma}{1-\sigma}}+\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_aA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right]}{\left[1-\left[\odot\right]^{\frac{\sigma}{1-\sigma}}\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\right]}.$$

So we have,

$$\frac{M_a}{T_a}\frac{\partial T_a}{\partial A_a}=M_a\frac{\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_aA_L^{'}(\theta)}{w_m}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\odot\right]^{\frac{\sigma}{1-\sigma}}+\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_aA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right]}{\left[1-\left[\odot\right]^{\frac{\sigma}{1-\sigma}}\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\right]}$$

and,

$$\frac{F_a}{T_a}\frac{\partial T_a}{\partial A_a}=F_a\frac{\left[\left[\frac{1}{\otimes}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_aA_L^{''}(\theta)}{w_f}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\left[\otimes\right]^{\frac{\sigma}{1-\sigma}}+\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_aA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right]}{\left[1-\left[\otimes\right]^{\frac{\sigma}{1-\sigma}}\left[\tau\right]^{\frac{\sigma}{1-\sigma}}\right]}.$$

Now,

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

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

$$\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a}<0\Leftrightarrow\left[\left[\frac{1}{\odot}\right]\left[\frac{\sigma}{1-\theta}\left[\frac{P_a(\theta)A_L^{'}}{w_m}\right]^{(1-\sigma)}(A_a)^{-\sigma}\right]<\left[\frac{1}{\tau}\right]\left[\frac{\sigma}{\theta}\left[\frac{P_aA_K(1-\theta)}{r}\right]^{(1-\sigma)}A_a^{-\sigma}\right]\right].$$

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

$$\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a}<0\Leftrightarrow\left[(\theta)^{\sigma}\left(\frac{w_m}{A_L^{'}}\right)^{(1-\sigma)}\right]-\left[(1-\theta)^{\sigma}\left(\frac{r}{A_K}\right)^{(1-\sigma)}\right]<0. \tag{B.28}$$

It is straightforward from above that

$$\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a}<0\Leftrightarrow\left(\frac{\theta}{1-\theta}\right)^{(\sigma)}\left(\frac{w_mA_K}{rA_L}\right)^{(1-\sigma)}<(\Omega)^{(1-\sigma)},$$

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

$$\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a}<0\Leftrightarrow\Omega>\left(\frac{\theta}{1-\theta}\right)^{\left(\frac{\sigma}{1-\sigma}\right)}\left(\frac{w_mA_K}{rA_L}\right)\equiv M.$$

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

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

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

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

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

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

Now if we have the following condition

$$\left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right) > 1, \tag{B.29}$$

we can verify that

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

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

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

and taking log on both sides of the inequality we get

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

Now if B.29 holds, we guarantee that

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

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

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

which gives us the following

$$M < \left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right). \tag{B.30}$$

Note that, this doesn't contradict with B.29 and given $M > 1$. Therefore, given $M > 1$, B.29, and B.30 hold, we can assert that

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

We can express it in the set form as shown below

$$\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(\frac{\log\left[M\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}, \infty\right). \tag{B.31}$$

Proof of part (c):
Note that

$$\frac{\partial\left(\frac{M_a}{F_a}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{\partial\left(\frac{\frac{M_a}{T_a}}{\frac{F_a}{T_a}}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{T_a}{F_a}\left[\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a} - \frac{M_a}{F_a}\cdot\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a}\right] > 0.$$

Given both T_a and F_a are strictly positive, the last inequality is equivalent to the condition

$$\frac{T_a}{M_a}\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a} > \frac{T_a}{F_a}\cdot\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a}.$$

Now, when we substitute the expressions for $\frac{\partial\left(\frac{M_a}{T_a}\right)}{\partial A_a}$ and $\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a}$ 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

$$\frac{\partial\left(\frac{M_a}{F_a}\right)}{\partial A_a} > 0 \Leftrightarrow \frac{\partial\left(\frac{\frac{M_a}{T_a}}{\frac{F_a}{T_a}}\right)}{\partial A_a} > 0 \Leftrightarrow \left[\frac{A_L^{'}}{w_m}\right]^{(1-\sigma)} < \left[\frac{A_L^{''}}{w_f}\right]^{(1-\sigma)} \Leftrightarrow \left[\frac{A_L^{'}}{w_m}\right] < \left[\frac{A_L^{''}}{w_f}\right] \qquad [\because \sigma < 1].$$

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:-

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

Given B.29, it can be verified that

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

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

$$0 < \alpha < \frac{1}{2}. \tag{B.32}$$

Therefore, under the conditions B.29 and B.32, we guarantee that

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

We can express it in the set form as shown below

$$\frac{\partial\left(\frac{M_a}{F_a}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right). \tag{B.33}$$

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.18, B.20, B.21, B.29, B.30 and B.32. It is straightforward that B.18 and B.30 jointly subsume the restriction B.29 and imply the restriction $1 < M < \left(\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right)$. This restriction taken together with B.21 actually sets a lower bound on $\frac{w_m}{w_f}$:

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

The assumption B.20 when $\epsilon < 1$ sets an extra lower bound on $\frac{w_m}{w_f}$:

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

which amounts to,

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

Moreover, $\frac{w_m}{w_f} > \frac{M}{(1-\alpha)^{\left(\frac{\epsilon}{\epsilon-1}\right)}}$ implies that $\epsilon < \frac{\log\left[\frac{w_f}{w_m}\cdot M\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{M}{1-\alpha}\right]}$ and this restriction on ϵ is contained within the result $\frac{\partial\left(\frac{F_a}{T_a}\right)}{\partial A_a} < 0 \Rightarrow \epsilon \in \left(0, \min\left[\frac{\log\left[\frac{w_f}{w_m}\cdot M\right]}{\log\left[\frac{w_f}{w_m}\cdot\frac{M}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha}\cdot\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha}\cdot\frac{w_m}{w_f}\right]}\right]\right)$. However, the same assumption B.20 along with $\epsilon > 1$ sets an upper bound on $\frac{w_m}{w_f}$:

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

Note that given B.32, when $(1-\alpha)^2 < \alpha$, that is, $\alpha \in \left(\frac{3-\sqrt{5}}{2}, \frac{1}{2}\right)$, we have

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

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

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

Since $\epsilon > 1 \Leftrightarrow \frac{\epsilon}{\epsilon-1} > 1$ given B.32, $(1-\alpha)^{\frac{\epsilon}{\epsilon-1}} < (1-\alpha)$ holds true. On the other hand, given B.32, when $(1-\alpha)^2 > \alpha$, that is, $\alpha \in \left(0, \frac{3-\sqrt{5}}{2}\right)$, we have

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

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

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

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

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

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.24, B.31, and B.33, must hold simultaneously for the economy, the following characterizes the set of values possible for ϵ:

$$\epsilon \in \left(\frac{\log[M]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \min\left[\frac{\log\left[\frac{w_f}{w_m} \cdot M\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right]\right) \tag{B.34}$$

where,

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

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, $\epsilon > 1$:

$$\epsilon \in \left(1, \min\left[\frac{\log\left[\frac{1-\alpha}{\alpha}\right]}{\log\left[\frac{(1-\alpha)^2}{\alpha}\right]}, \frac{\log\left[\frac{w_f}{w_m} \cdot M\right]}{\log\left[\frac{w_f}{w_m} \cdot \frac{M}{1-\alpha}\right]}, \frac{\log\left[\frac{\alpha}{1-2\alpha} \cdot \frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}, \frac{\log\left[\frac{w_m}{w_f}\right]}{\log\left[\frac{\alpha}{1-\alpha} \cdot \frac{w_m}{w_f}\right]}\right]\right). \tag{B.35}$$

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.34 and B.35. Hence the proof.

C Data Appendix

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

C.1 Construction of variables

C.1.1 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.[1] We detail the classification of implements from all sources of power by their operation type in the following manner. Primary tillage equipment consists of wooden plough, mould board plough, tractor driven mould board plough, rotavator, cultivator. Secondary tillage 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.

C.1.2 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.

C.1.3 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.

[1] 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.

C.1.4 Climate

Daily gridded datasets for rainfall (0.25ox0.25o grid) and temperature (1ox1o grid) have been obtained from the India Meteorological Department (IMD) for the years. 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 at grid points. 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.

C.1.5 Other agricultural controls

The Ministry of Agriculture's 'Land Use Statistics' 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).[2]

C.1.6 Socio-demographics

We 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.

C.1.7 Development controls

A district level variable for proportion of villages with a paved approach road 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. And, the annual district average nightlight luminosity is obtained by averaging over the pixels inside each district boundary.

[2]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.

C.2 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) were 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 in 2011 only 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 Surve data for 1993. Also, 3 districts do not report data on fertilizer use for 1998. The baseline 2SLS specification thus has 1073 district-year observations.