Agricultural Mechanization and Gendered Structural Transformation in India

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Abstract

We show that large-scale public works programs targeted at rural women are not sufficient to offset the decline in women's labor force participation driven by broader structural transformation. We examine the differential effects of agricultural mechanization on women's employment by leveraging the staggered roll-out of India's National Rural Employment Guarantee Scheme (NREGS), the world's largest public works program. By exploiting spatial and temporal variation in district soil texture and national trends in mechanization, we find that NREGS did not mitigate women's exit from the labor force spurred by agricultural mechanization. Instead, the mechanization-induced decline in women's labor force participation is larger in NREGS than in non-NREGS districts. On the intensive margin, NREGS did not influence the reduction in days worked by women per week. These findings highlight the limits of public works programs in counteracting gender-biased impacts of structural change.

Keywords: Structural transformation, agricultural mechanization, labor, gender, public policy, workfare programs, India

JEL Codes: J16, J21, J45, O13

1 Introduction

The Lewis (1954) dual sector model describes development as a process by which excess labor moves from a labor-intensive "subsistence" sector with lower wages to a modern "capitalist" sector (Gollin, 2014). However, the process of transformation is slow-moving and market imperfections can prevent its effects from reaching all sections of society. Following the liberalization in the Indian tractor industry in 1992, the agricultural sector saw a rapid increase in the level of mechanization in its production processes (Bhattarai et al., 2016). The expansion of mechanized tilling during this period has been shown to be directly responsible for the fall in female labor force participation (Afridi et al., 2023). This reflects the gendered nature of India's rural labor market, where men and women are imperfect substitutes and exhibit differing degrees of complementarity with mechanized agricultural equipment. Men, being the primary labor type used in land preparation, were displaced by the new capital but they were largely reabsorbed into new jobs in the modernized agricultural sector. In contrast, women — who are primarily employed in downstream tasks such as weeding and transplanting — were displaced by the introduction of mechanized tilling which reduced the need for these secondary tasks, but they were not sufficiently reabsorbed into the modern agricultural sector.

Agricultural growth is widely recognized as more effective at reducing poverty than growth in other sectors (Ligon and Sadoulet, 2018; Ivanic and Martin, 2018; Dorosh and Thurlow, 2018; Christiaensen and Martin, 2018). Productivity gains in agriculture can benefit rural households by lowering production costs, reducing food prices, and increasing labor demand and wages (Emran and Shilpi, 2018; Christiaensen and Martin, 2018). The labor channel is especially important in labor-abundant countries like India, but its effectiveness depends on the nature of technological change — whether it is labor or land-saving — and the availability of alternative non-agricultural employment opportunities.

This paper investigates whether the expansion of alternative female-friendly jobs opportu-

nities mitigated the fall in rural female labor force participation following the introduction of mechanized tilling. The roll-out of the National Rural Employment Guarantee Scheme between 2006 and 2008 is used a case study to investigate the validity of this hypothesis.

The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) was passed by the Indian Parliament and notified in 2005. The act led to the creation of state level public employment schemes which were collectively called the National Rural Employment Guarantee Schemes (NREGS) and which comprise the largest workfare program in the world (Sukhtankar et al., 2017). Under the schemes every adult member of a rural household is guaranteed 100 days of work every financial year. The act lays special emphasis on women's employment. One-third of all jobs created under the act are reserved for women. The schemes became operational in 200 of the poorest[1] districts during Phase 1 in February 2006. An additional 130 districts were included as part of Phase 2 in April and May 2007 and the remaining districts were added in April 2008.

We exploit the staggered roll-out of the NREGS to test whether the program being operational in a district reduced female job loss due to mechanization. Put another way, our objective is to examine if and to what extent the female labor displacing effects of agricultural mechanization would have been worse in a district in the absence of NREGS. Although there is some evidence showing that NREGS was effective in increasing overall rural female employment (Azam, 2012; Imbert and Papp, 2015), there is also evidence that NREGS by raising rural wages increased the adoption of labor-saving technologies in India (Bhargava, 2023). A key challenge in estimating a causal relationship between agricultural mechanization and female employment outcomes is accounting for unobserved heterogeneity that affects both. We instrument the variation in district mechanization levels by the product between the spatial variation in soil texture classes across districts and the temporal variation in

[1]The Planning Commission ranked all 447 districts from poorest to richest (Bhargava, 2023) and based the order of assignment to phases based on this. However, there were at least two known exceptions: areas facing Naxalite pressures were prioritized and each state had to have at least two districts in Phase I (Sukhtankar et al., 2017)

national mechanization level. Both of these variable are individually arguably exogenous to district level male and female employment outcomes. Our sample is composed of around 400 districts, making it safe to assume that district level factors will not affect the overall national average level of mechanization. Also, mechanized tilling by tractors, which is used for deep tilling, is possible in loamy soil but not clayey soil (Afridi et al., 2023; Carranza, 2014). But the soil texture only determines the depth of tillage and does not affect the quality or crop suitability of a soil (Carranza, 2014). Thus the instrument created as a product of these two variables satisfies the dual requirements of relevance and exogeneity. Instrumenting the area of district land under mechanized tilling by the product between the national average level of mechanization in a year and the difference in the share of loamy and clayey soil in a district we investigate the heterogenous effect of tractor adoption across NREGS and non-NREGS districts.

Our results indicate that in the absence of the workfare program a 10% increase in the area of land in a district operated on by tractors leads to a 2.4 percentage point reduction ($p<0.1$) in the likelihood of a woman participating in the rural labor force and a 1.7 point reduction ($p<0.1$) in the percentage of weekly days spent in private sector work. The workfare program while providing alternative work in the public sector also increases the number of women leaving private sector jobs in agriculture. We find that the workfare program led to a 3.5 percentage point increase ($p<0.05$) in the likelihood of a women exiting the agricultural labor force due to a 10% increase mechanized tilling. The program does increase the likelihood of a women being in the agricultural work force by 11 percentage point ($p<0.05$) irrespective of the districts level of mechanization, however it is not sufficient to compensate for lost work due to mechanization. These result are robust to controlling for unobserved invariant heterogeneity between NREGS and non-NREGS districts and a rich set of individual and district level controls.

In fact our findings suggest a substitution of men's work for women's work in rural India

as result of the combined effect of the creation of new public sector jobs for both men and women and a fall in women's work opportunities in the private sector.

We fail to find evidence that women in NREGS districts spend more days on public sector work with increasing level of mechanization. This may be because NREGS was not designed to target mechanization induced job loss in agriculture. While the NREGS promises 100 days of work to every rural household, it's effectiveness is constrained by capacity constraints in creating jobs (Sukhtankar et al., 2017). Our findings still suggest that creating female friendly job opportunities can increase women's participation in the work force. If workfare programmes like the NREGS can be targeted to districts experiencing faster adoption of labor saving technologies it can help alleviate women's job loss and improve the benefits to cost of expensive programmes like the NREGS.

This paper contributes to the literature on the gendered effects of agricultural mechanization and to the empirical literature on the effects of NREGS on rural employment. Recent work by Caunedo and Kala (2021) and Afridi et al. (2023) has shown that tractor adoption in India caused a decline in the demand for female labor in agriculture. Additionally, Afridi et al. (2023) find no evidence of women's labor shifting toward the non-farm sector. We exploit the staggered rollout of NREGS to examine heterogeneous effects of mechanization across districts with and without the programme. We find that in districts where NREGS provided additional jobs through public works projects, women shifted some of their workdays from agriculture into these new jobs. This suggests that the insufficient supply of non-agricultural jobs for women contributed to the overall decline in female labor force participation.

Early studies by Imbert and Papp (2015) and Azam (2012) showed that NREGS increased women's participation in public works projects. Imbert and Papp (2015) demonstrated that the introduction of NREGS led women to substitute private-sector work with public jobs. By studying the effects of mechanization and NREGS in a common framework, we show that NREGS on its own did not cause women to exit private-sector employment. Instead, the

ongoing process of mechanization pushed women out of private-sector jobs in both types of districts; when the workfare programme was operational, women substituted some of their lost private-sector workdays with NREGS jobs.

2 Context and Data

Figure 1 describes the timeline of the NREGS roll-out. NREGS was rolled out in the first 200 districts as part of Phase I in February 2006, in the next 130 districts as part of Phase II in May 2007 and in the remaining districts as part of Phase III in May 2008. For the present study, July 1999 to June 2000 is taken as the pre-intervention period and the post-intervention period is July 2007-June 2008. In the post-intervention period, the NREGS was operational in both Phase I and II districts but was yet to be adopted in Phase III districts. Phase I and II districts constitute the *treatment* group and phase III districts the *control* group. Mechanization in agriculture was in its nascent stage in the baseline, and adoption took off during the first decade of the twenty-first century (Afridi et al., 2023). Thus, the period of study is well-suited to both interventions, in that the baseline provides a snapshot when NREGS was not operational and mechanized tilling was minimal and the endline had both treatments operational to some degree in the sample.

For ease of exposition, we will refer to phase I and II as NREGS districts and phase III districts as non-NREGS districts henceforth.

2.1 Employment Measures

Data on employment is available from the nationally representative employment and unemployment surveys conducted by the National Sample Survey Organisation (NSSO). The employment rounds of the National Sample Survey (NSS) are conducted irregularly, with thick (larger sample) rounds and thin (smaller sample) rounds (Imbert and Papp, 2015). We use the 55^{th} (July 1999 - June 2000) and 64^{th} (July 2007 - June 2008) rounds because they

offer a representative sample and align with our period of study.

Using the data in the NSS, we create two measures of employment–at the extensive and at the intensive margins based on how the NSS measures employment. The extensive margin is measured based on the primary and subsidiary occupation of a person in the preceding year. The *primary occupation* is the economic activity a person spent the majority of the preceding year in. If there are multiple activities, the second-most performed activity is recorded as the *subsidiary occupation*. For an activity to qualify as a subsidiary occupation, a persons needs to be engaged in it for a minimum of 30 days but less than 6 months (Afridi et al., 2023). A person may be engaged in an economic activity as an employer or own-account worker in the family enterprise/farm (*Self-employed*); as an unpaid worker on the family enterprise/farm without autonomy on operations or management (*Unpaid family worker*); as a worker in private sector enterprises either as a casual wage worker or regular salaried worker (*Wage work*); or as a worker in government or public projects such as those created under NREGS (*Public work*). The sector of employment is adjudged to be agriculture or non-agriculture based on two-digit National Industry Classification (NIC) number for 2004 or 1998 depending on the year of the survey. A person engaged in an economic activity or seeking employment is considered as being in the labor force.

The intensive margin is measured using time-use data on the economic activities a person performed in the week preceding the survey. We measure the number of days a person spent on economic activities, and non-economic activities such as domestic work. Days spent on work is further classified into agricultural and non-agricultural sector work as well as the type of occupation (*Self-employed*, *Unpaid family labor*, *Wage work*, or *Public work*).

We only use observations from working age men and women, those aged 15-65, from the rural sector in our analysis.

2.2 Mechanization

District-level data on agricultural mechanization is obtained from the Input Census which is conducted every five years by the Indian Ministry of Agriculture.[2] There have been four rounds of the survey so far: 1996-97, 2001-02, 2006-07, 2011-12 and 2016-17. The Input Census rounds that align with the pre- and post-intervention periods the closest are the 1996-97, the 2001-02 and the 2006-07 rounds. However, the 2001-02 round has several missing observations and inconsistencies. Due to delays, the 1996-97 round was actually conducted over 1997-99. This round is used as the pre-intervention period before NREGS was rolled-out in any of the districts. The 2006-07 round is used to construct the post-intervention sample. The Input Survey reports the number of landholdings which use different farming implements–hand-driven, animal-driven, and power-operated implements. Following Afridi et al. (2023) we identify tractor drawn mouldboard ploughs, rotavators, and cultivators as power-operated primary tilling implements; and tractor drawn disc harrows, tractor drawn levellers and cagewheels are identified as secondary tilling implements. We calculate the percentage of total district land holdings under primary tilling and the percentage of total land holdings under secondary tilling. The mechanization variable is calculated as the sum of these two variables and thus takes values in the interval $[0, 200]$.

2.3 Soil Texture

Data on soil texture was obtained from the ISRIC World Soil Information Service (WoSIS) which hosts spatial maps of soil properties like texture for the entire globe. Specifically we use the SoilGrids 2.0 dataset which contains the fraction of sand, silt, and clay content in every 250mx250m cell at different soil depth (Poggio et al., 2021). We used the `gDalUtilities` library on R to download the spatial datasets hosted on ISRIC. Based on the mean fraction

[2]This data was downloaded from https://inputsurvey.dacnet.nic.in/ The website has migrated to a new address: https://inputsurvey.da.gov.in/, though the district tables are not visible yet.

of sand, silt, and clay in soil at a depth of 0-5 cm we use the `TT.points.in.classes` function in the R `soiltexture` library to classify each grid cell it into the 12 group classification for soil texture type available from the United States Department of Agriculture (USDA). These groups were further consolidated into either clayey, loamy and sandy soil classes.[3] We use GIS (Geographic Information System) boundary files for India obtained from IPUMS website to convert the spatial data into district-level observations suitable for our purposes.[4] The instrumental variable used to predict the degree of mechanized tilling by tractors in a district is the difference between the fraction of loamy soil and the fraction of clayey soil in a district.

2.4 Controls

2.4.1 Individual-level controls

Individual-level controls for a person's age, caste, religion, marital status, monthly per capita consumption expenditure, and land owned were obtained from the NSS survey rounds.

2.4.2 District-level controls

District-level controls used include controls for cropping patterns in a district, fertilizer (NPK) consumption, fraction of irrigated land, average landholding size, fraction of urban population, night lights intensity, rural female and male labor force participation rates in 1991, total monthly rainfall averaged on each quarter, maximum and minimum temperature in a quarter, proportion of district area under different soil depth classes, proportion of district area under different terrain slope classes and the mean pH level of district soil.

[3]Following Afridi et al. (2023) we classify clay loam, silty clay loam, silty clay, sandy clay and clay as clayey soil. Silt, loam, silty loam, sandy clay loam, sandy loam and clay loam are classified into loamy soil. Sand and loamy sand compose sandy soil. We diverge from Afridi et al. (2023) in one respect, while the cited paper distinguishes between coarse and fine clay loam, taking fine clay loam as clayey and coarse clay loam as loamy, we classify all clay loam soil as belonging to the clayey category of soils.

[4]The shapefile can be accessed at this link: https://international.ipums.org/international/gis_yrspecific_2nd.shtml.

The data on the rainfall and temperature were downloaded as spatial rasters from GAEZ (Global Agro Ecological Zones) data portal maintained by the FAO (Food and Agriculture Organization).[5] The fraction of each district area under various slope classes were also obtained as spatial rasters from *Bhuvan* which is the geo-portal of ISRO (Indian Space Research Organisation).[6] The data on the soil pH level and terrain slope were obtained as spatial rasters from the ISRIC WoSIS portal which is described above. All spatial data were converted to district-level observations using the GIS boundary file already described.

The Input Survey rounds in 1996-1997 and 2006-07 were not conducted for the states of Bihar, Jharkhand and Maharshtra. Therefore we exclude these districts from the analysis, leading to us dropping 81 of the 511 districts for which the 55^{th} round of the NSS has data. Additionally, we exclude eight districts which were completely urban and so not eligible for NREGS, these are Hyderabad, Delhi, Mumbai, Suburban Mumbai, Mahe, Yanam, Chennai and Kolkata. Eight districts had missing mechanization data and due to certain issues with the GIS boundary file another nine districts were dropped. In total we had 397 districts in the baseline which were used for the analysis. Official district boundaries changed between the baseline data and the endline datas. We mapped the 397 districts in the baseline to 456 districts in the endline. We cluster at the level of the districts in the endline because it was this district list which was used to determine Distribution across the different phases of the NREGS.

2.5 Descriptive Statistics

Table 1 presents the trends in the main employment and mechanization variables between 1999/00 and 2007/08. The percentage change between the two rounds were computed using district fixed effects OLS regressions. We have data from 404 districts out of which 124 are from the first phase of NREGS roll-out, 92 are from the second phase, and 194 are from the

[5]Data is available here: https://gaez.fao.org/.

[6]The dataset used is the NRSC Soil dataset. It is avialable here: https://bhuvan-app3.nrsc.gov.in/data/download/index.php?c=p&s=NI&g=all.

third phase. In 1999/00 NREGS was yet to be rolled out to any of the districts in India. In 2007/08, NREGS had become operational in first and second phase districts and these are the "NREGS Districts" while the third phase districts are the "Non-NREGS Districts". A person is considered to be "In labor force" if they reported as being engaged in an economic activity as either their primary or subsidiary occupation in the preceding year. A person is an "Ag. worker" if they were engaged in an agricultural activity as either their primary or subsidiary occupation. "Non-ag. worker" status is defined in an analogous manner. The jobs created under NREGS were typical of public employment schemes, including jobs in construction of public goods like roads and irrigation projects and jobs clearing land for cultivation (Sukhtankar et al., 2017). Thus, people engaged in these public sector jobs could either be "Ag. workers" or "Non-ag. worker". To better pick out the independent effect of NREGS we create the additional category "Public worker". A "Public worker" is a person who engaged in a government sponsored project such as those created under NREGS either as their primary or subsidiary occupation. "District area under mechanized primary tilling" and "District area under mechanized secondary tilling" are constructed as defined above. The total of these two numbers is the measure of *Mechanization* we use for the present analysis.

Usage of mechanized implements for tilling was minimal in the baseline. However, the Non-NREGS districts had a higher degree of mechanization than the NREGS districts. This discrepancy is explained by the targeted roll out of NREGS to less developed states first and more developed states in later phases. Tilling by mechanized means rose by a large degree between the baseline and endline. The increase was greater in the NREGS districts, perhaps due to purely mechanical reasons as there was more potential capacity to be added in these districts than the more affluent districts which already had a higher degree of mechanization. Another potential reason maybe that NREGS which led to rise in private sector wages also accelerated adoption of labor-saving capital goods. Bhargava (2023) shows that this phenomenon did take place, however it was mainly limited to the adoption of

animal-operated technology groups rather than power-operated ones which is the main focus of this study.

Women saw a fall in labor force participation in the whole sample, though the male labor force participation rate remained largely unchanged. In fact, men in NREGS districts experienced a moderate increase in labor force participation rates. Both men and women saw a considerable rise in participation rates in the non-agricultural sector. However, for women since non-agricultural jobs were quite rare in the baseline this increase though large in percentage terms was insufficient to counter the fall in agricultural jobs. Men saw a rise in agricultural job participation rates as well as non-agricultural job participation rates. Women as a whole also experienced a fall in public sector jobs which includes jobs created under NREGS. Strangely, even in the NREGS districts there was fall in the number of women who were public workers though the fall is smaller than in the Non-NREGS districts. There was a large rise in the male participation in public jobs in the NREGS districts though in the Non-NREGS districts there was a fall.

However, upon examining the intensive margin of employment there is evidence that NREGS led to large increases in the number of days spent on public sector work in the districts where it was operating. The increase was larger for women than men, though both sexes spent a very small fraction of weekly working days on public sector work. Both men and women experienced declines in the share of weekly days spent on agricultural or non-agricultural work whereas the share of domestic work increased for women in both NREGS and Non-NREGS districts and for men in the Non-NREGS districts.

These figures suggest that while agriculture saw a rise in the adoption of improved tilling technology there was an overall fall in rural female labor force participation rates even though male labor force participation remained unchanged or even rose in certain areas. The districts with NREGS saw a rise in male public workers though women public workers fell. However, NREGS seems to have had some effect for women as well since the fall in public workers in

NREGS districts was smaller than in the Non-NREGS districts. In terms of days worked, NREGS districts saw large increases in the category of public work while private sector work hours fell for both men and women. Overall it appears that while NREGS did increase female days worked, it may not been sufficient to offset the fall due to mechanized tilling.

3 Methodology

Mechanization in agriculture, specifically mechanization in tilling is a continuous process that has been shown to reduce female labor force participation over time (Afridi et al., 2023). Conversely, the NREGS is the world's largest workfare workfare programme which led to increased female non-farm employment opportunities through its guarantee of 100 days of work at minimum wages for every adult in a rural household (Imbert and Papp, 2015; Azam, 2012; Sukhtankar et al., 2017). We will use individual-level data on employment statistics to examine if NREGS mediated the labor-displacing effect of mechanized tilling by offering alternative forms of employment for women pushed out of the agricultural private sector.

To that end we will estimate the following specification using repeated cross-sections from a period before NREGS implementation (1999/00) and from a period when NREGS had been implemented in a subset of districts (2007/08):

$$Y_{idt} = \beta_1 M_{dt} + \beta_2 \mathbb{1}_{NREGS\ Active} + \beta_3 M_{dt} \times \mathbb{1}_{NREGS\ Active} + X'_{idt}\beta_4 + \theta_d + \mathbb{1}_t + \epsilon_{idt} \quad (1)$$

where Y_{idt} is the relevant dependent variable which includes extensive measures of employment which are labor force participation status (0/1), agricultural worker status (0/1), and non-agricultural worker status of individual (0/1); and intensive measures of employment which are percentage of days worked in a week, percentage of days in a week spent on

private sector agricultural work, and percentage of days in a week spent on public sector work (like those provided under NREGS) for individual i in district d at time t; M_{dt} is the mechanization level in district d at time t; $\mathbb{1}_{NREGS\ Active}$ is an indicator variable for wether NREGS is operational in district d at time t; X_{idt} is a vector of both individual and district level controls; θ_d are the district fixed effects; $\mathbb{1}_t$ is an indicator variable for the endline and ϵ_{idt} is the random error. To account for correlated errors within districts, standard errors are clustered at the district level. We include individual level controls for age, education, marital status, religion, caste, owned land and monthly consumption expenditure. District level controls include soil characteristics like pH level, slope of the terrain, depth; ecological controls for temperature and precipitation; and the fraction of district population that is urban.

In equation 1, the coefficient β_1 measures the effect on employment of an additional percentage of district land under either primary or secondary tilling equipment. We expect $\beta_1 < 0$ when the dependent variable is labor force participation, agricultural worker status, days worked in a week, or days in agricultural private sector work. β_2 measures the independent effect of NREGS operating in a district on the employment measures. It is expected that $\beta_2 > 0$ for the dependent variable days of public sector work, and for female labor force participation status if NREGS is successful in increasing overall labor force participation for women. β_3 tells us of the additional effect of the availability of NREGS jobs with a percentage point increase in the level of agricultural mechanization in a district. If women are more likely to accept NREGS jobs as agricultural mechanization increases we would expect $\beta_3 > 0$. Whether NREGS was successful in offsetting job loss due to mechanized tilling can be judged by the relative magnitudes of β_1, β_2, and β_3.

NREGS was rolled out in a staggered manner across districts, providing us with a counterfactual in late phase districts which were yet to receive NREGS in the endline. However, the roll out across districts was not randomized. To account for this, we include district

level fixed effects in the above specification which control for unobserved differences between early and late adopters of NREGS. However, in order to estimate the mediating effect of the NREGS on the fall in female employment opportunities due to agricultural mechanization one also must take into account of the possibility of reverse causality affecting the relationship between the mechanization and female employment. Additionally, the two treatment variables could have affected each other. Specifically, NREGS which created jobs in the public sector offered a fixed and competitive wage to workers, this could have in turn accelerated the adoption of labor-saving technology if supply side factors pushed up private sector wages.

One way of measuring the heterogeneous effects of mechanization on women's labor outcomes based on NREGS status, is to predict mechanization level using the exogenous variations in a variable which is arguably not linked directly to either female labor market outcomes or the order in which NREGS was rolled out across districts. We propose that a district's distribution of soil texture fulfills both these requirements. Namely, the share of district soil that is loamy and the share that is clayey affects the soil's suitability to tilling by tractors. Mechanized tilling by tractors is used for primary or deep tilling which is possible in loamy but not clayey soil (Afridi et al., 2023; Carranza, 2014). Crucially, the soil texture only determines the depth of tillage and does not affect the quality or crop suitability of a soil (Carranza, 2014). Soil texture is therefore arguably exogenous to female labor outcomes.

Since both mechanization level and NREGS are right hand side variables, robustness to endogeneity concerns does not require independence between the two treatments. In fact, we expect there to be some relationship between the two thereby making it crucial to account for both these economic forces. However, if the two treatments are highly correlated it can lead to multicollinearity concerns which can make getting precise estimates of either of the two treatment variables difficult. NREGS rollout was based on a ranking of the 447 poorest districts by the Indian Planning Commission (IPC) using mid-1990s data on wages,

productivity, and fraction of scheduled castes and tribes. Given that the soil texture in a district does not directly affect agricultural productivity, it is unlikely to be directly linked with any of the deciding factors for NREGS rollout. This helps ensure that the variation in mechanization used in our regression represents only the variation due a mechanical property of the soil which is exogenous to any factor which may have affected NREGS roll out as well as being exogenous to general equilibrium effects on wages arising due to NREGS adoption.

One drawback to instrumenting district-level mechanization by the variation in district area that is clayey and loamy soil is that it produces local average treatment effects which rely solely on spatial variation. As alluded to previously, we rely on a difference-in-difference strategy to control for the non-randomized roll-out of the NREGS. As a result, we are concerned with changes over time and soil texture being an ecological property does not vary over a time of reference as short as ours. To accommodate the variation in district-level tractor adoption rates over time in the instrument, we construct it as the product of the district soil texture measure and the national average share of district area under mechanized tilling. Since the measure for mechanization is a national average it is unlikely to be affected by district-level factors and is arguably exogenous.

We estimate the following specification using repeated cross-sections for 1999/00 and 2007/08:

$$Y_{idt} = \beta_1^1 M_{dt} + \beta_2^1 \mathbb{1}_{NREGS\ Active} + \beta_3^1 M_{dt} \times \mathbb{1}_{NREGS\ Active} + X'_{idt}\beta_4^1 + \theta_{NREGS} + \theta_s + \mathbb{1}_t + \epsilon_{idt} \quad (2)$$

where M_{dt} is now predicted using AS_{dt} which is the augmented soil texture variable and is constructed as the produced between the national average district level of mechanization in year t and the difference between the share of soil which is loamy and the share which is clayey

in district d. Since the instrument AS_{dt} only captures the national trend in mechanization levels over time, including district-level fixed effects is not feasible since it captures much of the variation in the instrument. To account for the non-random roll-out of the policy, we include fixed effects at the NREGS group level, θ_{NREGS}, which is a dummy variable equal to unity for phase I and phase II NREGS districts irrespective of the year. We also include state level fixed effects θ_s to account for unobserved time-invariant confounders at the state level.

The first stage regressions are given by:

$$M_{dt} = \beta_1^2 AS_{dt} + \beta_2^2 \mathbb{1}_{NREGS\ Active} + \beta_3^2 AS_{dt} \times \mathbb{1}_{NREGS\ Active} + X'_{idt}\beta_4^2 + \theta_{NREGS} + \theta_s + \mathbb{1}_t + \epsilon_{idt}$$

and,

$$M_{dt} \times \mathbb{1}_{NREGS\ Active} = \beta_1^3 AS_{dt} + \beta_2^3 \mathbb{1}_{NREGS\ Active} + \beta_3^3 AS_{dt} \times \mathbb{1}_{NREGS\ Active} + X'_{idt}\beta_4^3 + \theta_{NREGS} + \theta_s + \mathbb{1}_t + \epsilon_{idt}$$

While we account for both time variant heterogeneities at the NREGS district group level and state level, our estimated effects should be interpreted as the heterogenous effects of mechanization under NREGS non-operational and NREGS operational conditions. The present exercise aims to observe the effects of agricultural mechanization in the presence and absence of rural workfare programmes rather than identify the causal effect of NREGS on employment which has been studied previously (Imbert and Papp, 2015; Azam, 2012; Sukhtankar et al., 2017).

4 Results

4.1 First Stage

Table 2 shows the first stage results from the IV regression of mechanization and NREGS on employment outcomes for the sample of women and the sample of men. The instrument, *Soil texture* is constructed as the product of the national average mechanization level in a district and the difference between the share of loamy and the share of clayey soil in a district. *NREGS Active* is an indicator for whether the workfare program is operation in a district at the given time period.

We are able to reject the null of weak identification individually for both *Soil texture* and *Soil texture*NREGS Active*. For both the sample of women (Columns 1 and 2) and men (Columns 3 and 4), we reject the null that the maximal bias for either of the individual instruments (*Soil texture* and *Soil texture*NREGS Active*) is greater than 15% of the bias under OLS. The null for overall weak identification is tested using the Kleibergen-Paap Wald F statistic since our estimates are robust to clustering. For the sample of women this statistic is equal to 9.49 and for the sample of men it is 8.93. These figures are greater than the Stock-Yogo critical value for greater than 10% of OLS bias.

4.2 Extensive Margin

The results from the second-stage regression of labor force participation status on mechanization and NREGS status are presented in columns 1 and 4 in Table 3.

The dependent variable is an indicator function for whether an individual is in the labor force. This variable was multiplied by a factor of 100 in order to able to interpret the estimates as percentage points. In the absence of the program, a percentage point increase in district land area under either primary or secondary tilling by machines led to a 0.25 percentage point fall ($p<0.1$) in the probability of a woman being in the labor force. The

program surprisingly increases the labor displacing effect of mechanization by 0.34 percentage points ($p<0.05$). The estimated independent effect of the program on women's labor force participation is large in magnitude but not very precise. The NREGS operating in a district leads to a 9 percentage point increase ($p<0.1$) in the probability of a woman being in the labor force.

Columns 2 and 3, break down labor force participation by whether a person is engaged in the agricultural or non-agricultural sector. The effect of mechanization on women's work opportunities is understandably isolated to agricultural jobs. The program has an independent positive effect on women's work in the agricultural sector even though it increases the labor displacing effect of mechanization.

The average mechanization level in the sample is approximately 27%. This level of mechanized tilling would displace 7% of women from the labor force and 6% of women from jobs in agriculture. At that level of mechanization, the program increases the number of women exiting jobs altogether and agricultural jobs by 9 percentage points each. The program also increases the likelihood of women's labor force participation and of working in agriculture, irrespective of the mechanization level, by 9% and 11% respectively. So the overall effect is a 7 percentage point fall in women's labor force participation rate and a 4 percentage fall in the share of women in agricultural jobs. Hence the workfare program seems to not be able to fully address the labor displacing effect of mechanization for women.

[Say something about negative interaction term]

Columns 4-6, show that in contrast to it's effect on women's work opportunities, mechanization did not have any significant impact on men's work status.

4.3 Intensive Margin

The *NSS* reports how many days in the past week a respondent spent on different types of activtives. This is used to construct the intensive measure of employment which is regressed

on mechanization and *NREGS* status.

Table 4 reports these results for the sample of women. Column 1 reports the results for the percentage of days spent on market-based economic activities which includes working on the family farm or enterprise but excludes domestic work. Similar to the situation with the extensive measures, the workfare program increases the labor displacing effect of mechanization. If NREGS is operational, a unit percentage increase in a district's mechanization level causes a 0.46 percentage point decrease ($p<0.01$) in share of days worked in a week.

Columns 2, 4 and 5 decompose days worked into private sector, public sector and domestic work respectively. Mechanization leads to a substitution of public sector and domestic work for private sector work, especially private sector agricultural work. This process was accelerated by the introduction of the workfare program which provides alternative employment not sensitive to agricultural mechanization.

Table 5 presents the analogous estimates for the sample of men. There is no effect of mechanization on job displacement for men. However in districts with higher mechanization levels, fewer men gravitate to public sector jobs under NREGS. This is likely because agricultural jobs provided greater remuneration than the public sector jobs. Men's jobs in agriculture are in a sense complementary to tractors, as they are more likely than women to be hired to operate the new tractors (Afridi et al., 2023).

Taken together, the greater labor displacing effect of mechanization for women under NREGS and the new public sector jobs for both men and women under the workfare program seems to have led to a substitution of men's work outside the house for women's work.

5 Conclusion

This paper examines whether the insufficient supply of female labor opportunities in the non-agricultural sector contributed to the fall in women's labor force participation due to

mechanization in the agricultural production process in India. Using the roll out of the NREGS as a case study, we show that districts which had the workfare programme saw a substitution in female work days from agriculture to public work projects. We use a two stage least squares regression, instrumenting tractor adoption rates by the exogenous variation in soil textures across districts and the variation in national average mechanization rates over time.

We show that even though the program created new work opportunities, it also hastened the exit of women from private sector agricultural work. The shortfall in women's labor in agriculture was likely compensated for by the new technology and by men's labor which did not see a fall in the private agricultural sector due to mechanization. In fact men's work opportunities on the whole expanded as they also enjoyed the benefits of the additional public sector jobs created under NREGS. Overall, there appears to have been a substitution of male labor for female labor in rural India during the period of this study.

While the NREGS is intended to provide 100 days of work to ever rural household in India, it is widely accepted that job supply constraints have affected its efficacy (Sukhtankar et al., 2017). This may be the reason that we don't find that women's employment in public sector jobs do not go up with increasing levels of mechanization across districts. Our results suggest that female friendly labor opportunities can reduce the fall in female labor and if programmes like the NREGS can be targeted to districts with greater adoption of labor saving technologies it can better reduce the fall in women's labor outcomes and improve the benefit-cost of public outlay into similar programmes.

Figure 1: Timeline of the NREGS

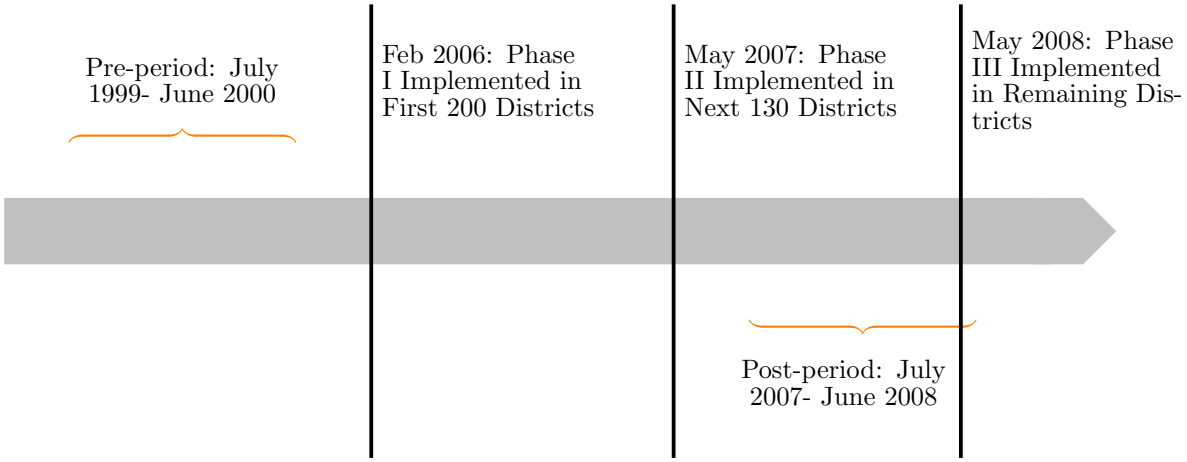


Table 1: Trends in employment and mechanized tilling between baseline (1999/00) and endline (2007/08).

	Whole sample		NREGS Districts		Non-NREGS Districts	
	1999/00 Mean (SE)	2007/08 Change (%)	1999/00 Mean (SE)	2007/08 Change (%)	1999/00 Mean (SE)	2007/08 Change (%)
District area under mechanized:						
Primary tilling (%)	6.206 (0.793)	201.03***	3.592 (0.923)	282.57***	8.704 (1.283)	175.54***
Secondary tilling (%)	10.956 (0.986)	87.22***	5.152 (0.757)	163.42***	16.770 (1.840)	65.91***
Mechanization	17.162 (1.648)	128.38***	8.744 (1.564)	212.36***	25.475 (2.911)	103.37***
Women:						
In labor force (%)	44.645 (0.421)	-3.87**	45.875 (0.563)	-3.62	43.335 (0.598)	-4.57
Ag. worker (%)	36.784 (0.398)	-5.27**	37.744 (0.516)	-3.13	35.802 (0.590)	-8.53**
Non-ag. worker (%)	7.152 (0.143)	26.46***	7.469 (0.197)	25.80***	6.762 (0.194)	27.06***
Public worker (%)	1.348 (0.065)	-68.85***	1.390 (0.090)	-53.06***	1.273 (0.084)	-90.61***
Days in week spent on:						
Pvt. ag. work (%)	26.772 (0.322)	-12.01***	28.544 (0.410)	-14.38***	24.770 (0.487)	-8.95**
Pvt. non-ag. work (%)	22.442 (0.284)	-7.61***	22.580 (0.351)	-9.44***	22.483 (0.447)	-5.75
Public work (%)	0.104 (0.037)	323.76***	0.117 (0.064)	474.92***	0.083 (0.017)	71.52*
Domestic work (%)	56.864 (0.368)	4.68***	55.682 (0.475)	5.63***	58.121 (0.541)	3.77**
Men:						
In labor force (%)	85.879 (0.135)	0.46	86.235 (0.187)	1.32***	85.306 (0.177)	-0.59
Ag. worker (%)	56.662 (0.298)	2.71***	58.493 (0.419)	5.52***	54.152 (0.379)	-0.89
Non-ag. worker (%)	27.552 (0.281)	33.17***	26.014 (0.400)	39.81***	29.470 (0.352)	25.62***
Public worker (%)	0.482 (0.061)	92.57***	0.446 (0.101)	196.55***	0.496 (0.045)	-15.99***
Days in week spent on:						
Pvt. ag. work (%)	61.382 (0.275)	-8.55***	63.106 (0.386)	-9.27***	59.207 (0.361)	-7.65***
Pvt. non-ag. work (%)	61.842 (0.239)	-1.71**	60.923 (0.319)	-1.64	63.119 (0.340)	-1.95*
Public work (%)	0.315 (0.049)	158.65***	0.318 (0.080)	271.06***	0.286 (0.030)	15.08
Domestic work (%)	1.300 (0.058)	30.96***	1.465 (0.083)	18.89*	1.076 (0.074)	52.08***
	1999/00	2007/08	1999/00	2007/08	1999/00	2007/08
Number of districts	404		210		194	
Number of women	90424	95558	51717	54648	42356	40910
Number of men	92261	94459	52531	54416	43248	40043

Notes: All estimates are from district fixed effects regression models. Percentage changes are calculated as 100 * coefficient on year dummy/constant. Standard errors were clustered at district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2: Results of first stage regressions for sample of women and men.

	Women		Men	
	Mechanization	Mech.*NREGS	Mechanization	Mech*NREGS
	(1)	(2)	(3)	(4)
Soil texture	0.462***	-0.055	0.426***	-0.059
	(0.110)	(0.042)	(0.110)	(0.040)
*Soil texture*NREGS Active*	-0.240**	0.368***	-0.205*	0.372***
	(0.110)	(0.104)	(0.107)	(0.098)
Constant	-111.240**	-62.423	-100.147*	-58.400
	(52.816)	(43.679)	(51.099)	(41.137)
Year FEs	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes
Ind. and dist. controls	Yes	Yes	Yes	Yes
R^2	0.643	0.401	0.641	0.402
Clusters	456	456	456	456
Individuals	182838	182838	183290	183290
Weak IV tests:				
	Soil texture	*Soil text.*NREGS*	*Soil texture*	*Soil text.*NREGS*
Sanderson-Windmeijer F stat.[a]	18.24	15.83	16.42	19.12
	Overall		Overall	
Kleibergen-Paap F stat.[b]	9.49		8.93	

Notes: Soil texture variable is constructed as the product between the national average level of mechanization in a district and the difference between the share of loamy and share of clayey soil in the district. Individual level controls for age, education, marital status, caste, religion, size of land owned by household, and monthly per capital consumption expenditure were included in each specification. District level controls for minimum temperature, maximum temperature, and average rainfall in a quarter; fraction of urban population; fraction of SC, ST and OBC households in the baseline; and average land holdings size. Standard errors clustered at district-level reported in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

[a] Sanderson-Windmeijer multivariate F statistic for testing if individual instruments are weak. The Stock-Yogo critical values for 10% and 15% maximal bias are 19.93 and 11.59 respectively.

[b] Kleibergen-Paap Wald rk F statistic for testing overall weak identification. Under i.i.d. the Stock-Yogo critical value for 10% maximal bias is 7.03.

Table 3: Results from second stage regression of annual work status mechanization and NREGS.

	Women			Men		
	LFP[a]	Ag. Worker[b]	Non-Ag. Worker[c]	LFP[a]	Ag. Worker[b]	Non-Ag. Worker[c]
	(1)	(2)	(3)	(4)	(5)	(6)
Mechanization	-0.251*	-0.218*	-0.009	-0.016	0.073	-0.136
	(0.134)	(0.127)	(0.045)	(0.034)	(0.079)	(0.093)
*Mech.*NREGS Active*	-0.343**	-0.350**	-0.029	0.024	0.012	0.147
	(0.168)	(0.158)	(0.045)	(0.035)	(0.078)	(0.090)
NREGS Active	9.073*	10.983**	0.355	0.535	3.088	-1.298
	(5.329)	(4.971)	(1.414)	(1.046)	(2.315)	(2.690)
Constant	80.987*	56.753	39.479	49.630***	72.286***	-7.163
	(49.089)	(42.143)	(27.339)	(11.324)	(24.809)	(28.677)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
NREGS Group FEs	Yes	Yes	Yes	Yes	Yes	Yes
Ind. and dist. controls	Yes	Yes	Yes	Yes	Yes	Yes
*Mech. + Mech.*NREGS*[d]	-0.549***	-0.568***	-0.035	-0.004	0.079	0.014
Avg. mechanization	27.271	27.271	27.271	27.081	27.081	27.081
Kleinbergen-Paap F Stat.	9.877	9.877	9.877	8.930	8.930	8.930
R^2	0.105	0.156	0.050	0.189	0.249	0.157
Clusters	456	456	456	456	456	456
Individuals	182838	182838	182838	183290	183290	183290

Notes: Individual level controls for age, education, marital status, caste, religion, size of land owned by household, and monthly per capital consumption expenditure were included in each specification. District level controls for minimum temperature, maximum temperature, and average rainfall in a quarter; fraction of urban population; fraction of SC, ST and OBC households in the baseline; and average land holdings size were included in each specification. Standard errors clustered at district-level reported in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

[a] The dependent variable is an indicator variable for whether an individual is in the labor force. This variable was multiplied by 100, so that the estimates can be interpreted as percentage points.

[b] The dependent variable is an indicator variable for whether an individual is engaged in the agricultural sector. This could be in the capacity of a wage laborer, family worker, worker on public projects or self-employed. This variable was multiplied by 100, so that the estimates can be interpreted as percentage points.

[c] The dependent variable is an indicator variable for whether an individual is engaged in the non-agricultural sector. This variable was multiplied by 100, so that the estimates can be interpreted as percentage points.

[d] The stars denote significance levels from a Wald chi-squared test.

Table 4: Results from second stage regression of percentage of women's weekly days spent on productive activities on mechanization and NREGS.

	(1) Total[a]	(2) Pvt.[b]	(3) Pvt. Ag.[c]	(4) Public[d]	(5) Dom.[e]
Mechanization	-0.168	-0.172*	-0.170*	0.012**	0.240**
	(0.103)	(0.101)	(0.097)	(0.006)	(0.119)
*Mech.*NREGS Active*	-0.294**	-0.273**	-0.279**	-0.016	0.297*
	(0.141)	(0.137)	(0.136)	(0.011)	(0.158)
NREGS Active	6.557	5.186	5.490	0.920**	-7.494
	(4.392)	(4.293)	(4.296)	(0.360)	(5.032)
Constant	51.965	40.559	30.044	7.738*	-4.655
	(47.268)	(45.789)	(42.685)	(4.325)	(48.008)
Year FEs	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
NREGS Group FEs	Yes	Yes	Yes	Yes	Yes
Ind. and dist. controls	Yes	Yes	Yes	Yes	Yes
*Mech. + Mech.*NREGS*[f]	-0.462***	-0.445***	-0.449***	-0.004	0.537***
Avg. mechanization	27.271	27.271	27.271	27.271	27.271
Kleinbergen-Paap F Stat.	9.595	9.595	9.595	9.595	9.595
R^2	0.095	0.087	0.100	0.005	0.116
Clusters	456	456	456	456	456
Individuals	182838	182838	182838	182838	182838

Notes: Individual level controls for age, education, marital status, caste, religion, size of land owned by household, and monthly per capital consumption expenditure were included in each specification. District level controls for minimum temperature, maximum temperature, and average rainfall in a quarter; fraction of urban population; fraction of SC, ST and OBC households in the baseline; and average land holdings size were included in each specification. Standard errors clustered at district-level reported in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

[a] The dependent variable is the percentage of days in the last week that the respondent spent working. This does not include domestic work but does include working on the family farm or enterprise.

[b] The dependent variable is the percentage of days in the last week that the respondent spent on private sector work.

[c] The dependent variable is the percentage of days in the last week that the respondent spent on private sector agricultural work. This could be in the capacity of a wage laborer, family worker, worker on public projects or self-employed.

[d] The dependent variable is the percentage of days in the last week that the respondent spent on public sector work.

[e] The dependent variable is the percentage of days in the last week that the respondent spent on domestic work.

[f] The stars denote significance levels from a a Wald chi-squared test.

Table 5: Results from second stage regression of percentage of men's weekly days spent on productive activities on mechanization and NREGS.

	(1) Total[a]	(2) Pvt.[b]	(3) Pvt. Ag.[c]	(4) Public[d]	(5) Dom.[e]
Mechanization	0.033	0.019	-0.005	0.012	0.003
	(0.054)	(0.056)	(0.065)	(0.009)	(0.012)
*Mech.*NREGS Active*	0.009	0.062	0.019	-0.041**	0.002
	(0.047)	(0.054)	(0.063)	(0.017)	(0.015)
NREGS Active	0.957	-2.249	-1.871	1.885***	-0.377
	(1.483)	(1.694)	(2.014)	(0.521)	(0.499)
Constant	1.354	-6.452	11.236	8.055	12.973**
	(15.147)	(17.144)	(27.317)	(5.092)	(6.362)
Year FEs	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
NREGS Group FEs	Yes	Yes	Yes	Yes	Yes
Ind. and dist. controls	Yes	Yes	Yes	Yes	Yes
*Mech. + Mech.*NREGS*[f]	0.389	0.081	0.050	2.143	0.062
Avg. mechanization	27.081	27.081	27.081	27.081	27.081
Kleinbergen-Paap F Stat.	8.720	8.720	8.720	8.720	8.720
R^2	0.206	0.188	0.192	0.005	0.013
Clusters	456	456	456	456	456
Individuals	183290	183290	183290	183290	183290

Notes: Individual level controls for age, education, marital status, caste, religion, size of land owned by household, and monthly per capital consumption expenditure were included in each specification. District level controls for minimum temperature, maximum temperature, and average rainfall in a quarter; fraction of urban population; fraction of SC, ST and OBC households in the baseline; and average land holdings size were included in each specification. Standard errors clustered at district-level reported in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

[a] The dependent variable is the percentage of days in the last week that the respondent spent working. This does not include domestic work but does include working on the family farm or enterprise.

[b] The dependent variable is the percentage of days in the last week that the respondent spent on private sector work.

[c] The dependent variable is the percentage of days in the last week that the respondent spent on private sector agricultural work. This could be in the capacity of a wage laborer, family worker, worker on public projects or self-employed.

[d] The dependent variable is the percentage of days in the last week that the respondent spent on public sector work.

[e] The dependent variable is the percentage of days in the last week that the respondent spent on domestic work.

[f] The stars denote significance levels from a a Wald chi-squared test.

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