Disaggregated labor supply implications of guaranteed employment in India

Megan Sheahan, Industrial Economics, msheahan@indecon.com
Yanyan Liu, International Food Policy Research Institute (IFPRI), y.liu@cgiar.org
Sudha Narayanan, Indira Gandhi Institute of Research Development (IGIDR), sudha@igidr.ac.in
Christopher B. Barrett, Cornell University, cbb2@cornell.edu

September 2020

Abstract: How do household labor supply decisions change with the entry of a massive employment guarantee program? This paper explores the household labor allocation effects – disaggregated by gender, age group, task, and season – associated with India's Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS). Using three rounds of panel household survey data combined with project administrative records in Andhra Pradesh, our results suggest that participation in MGNREGS prompted an increase in overall household labor supply by about 12 days only in the summer slack labor season, mostly attributed to adult women. This expansion is not large enough to evade "crowding out" of some labor previously offered to non-MGNREGS labor tasks, and more so in the main agricultural seasons than the summer slack season. Time spent on paid and unpaid activities do not increase for youth and children in MGNREGS-participating households, suggesting no within-household substitution of labor towards younger members.

Key words: labor, employment guarantee, public works, gender, MGNREGS, India

JEL codes: D13, E24, J22, J38, J45

Acknowledgements: We gratefully acknowledge funding from the International Initiative for Impact Evaluation (3ie), CGIAR Research Program on Policies, Institutions, and Markets (PIM), and Tata Cornell Initiative. We also thank Maribel Elias for assistance as well as Vidhya Soundararajan and seminar participants at Cornell University as well as the Agricultural and Applied Economics Association meeting for their insightful comments.

1. Introduction

Major government employment schemes, often in the form of public works projects, aim to provide income transfers to the poorest subpopulations, who have few employment options and whose low opportunity cost of time often induces them to work for low wages. Public works programs have historically been effective both as a safety net against shocks and as a self-targeting poverty alleviation strategy, while also addressing socio-economic inequalities and stimulating economic growth (Subbarao, et al., 2012; Sakketa and von Braun, 2019). Yet little research addresses how households respond to such programs. By altering the employment options available to a household, public works programs may alter overall household labor supply as well as task- and member-specific time allocation, with ambiguous impacts on net labor supply of individuals and the household.[1] Household labor allocation in response to such programs not only affects the net benefits that households derive but also has implications for the labor market overall. The case of India's Mahatma Gandhi National Rural Employment Guarantee Scheme (hereafter, MGNREGS) is no different, apart from the unique constitutional "right to work" under-pinning its implementation. The massive scope of the scheme – inclusive of all rural areas of India and employing around 50 million people every year (Khera 2011) – however suggests the potential for more extensive labor market effects and for a range of complementary shifts in how particular groups of individuals spend their time. The introduction of MGNREGS offers households, particularly poor households, the opportunity to reassemble their labor supply portfolio.

This paper explores various household level labor supply effects induced by participation in MGNREGS. Specifically, we investigate two policy-relevant questions. First, how does MGNREGS participation affect total household labor supply and the allocation of time to specific tasks? Do these effects vary by gender and age of the household member/worker or agricultural season? Second, does one day of work devoted to a MGNREGS project "crowd out" (or "crowd in") time spent on paid and unpaid work at the household level? Again, does disaggregating by gender, task, or season reveal any important patterns?

[1] These programs are similar but not identical to the increasingly popular conditional cash transfer (CCT) programs where income is provided to targeted households conditional on some outcome or action. Indeed, government employment schemes can be considered a special case CCT program whereby the conditioning mechanism is work.

MGNREGS participation may alter overall household labor supply, the allocation of time to specific paid and unpaid work, and the gender and age composition of non-MGNREGS work. Policymakers are keen to learn the various implications of MGNREGS employment for several reasons. Most obviously, the program has the potential to "crowd out" time previously allocated to work in the private sector, causing newfound constraints in the labor market and potentially no increase in the aggregate amount of time worked by individual laborers. There are fears that such crowding out, should it exist, would adversely affect agriculture specifically, a highly labor-intensive industry in India. One could also imagine how MGNREGS participation may "crowd in" other types of work, including time spent on household enterprises or own-farm, especially where MGNREGS wages can be used to invest in these endeavors. Policy makers may view this latter case as a positive outcome where these activities are highly productive and growth-inducing.

Moreover, the equality in wages offered to males and females via MGNREGS – in addition to a number of other program features that make it particularly attractive to women – may generate widespread female participation. Where women have historically undertaken much of the home-based unpaid work, female MGNREGS participation could prompt a shift in some of those tasks towards other household members, including youth and children who may be pulled out of school as a result. On the other hand, adult MGNREGS participation could bring more income into the household and reduce the need for younger members to participate in paid work. How these opposing forces net out is an important empirical question thus far unexplored. Ultimately, the decision to participate in MGNREGS could bring about a range of important labor supply outcomes that may differ by gender, age group, and task.

We employ three-round household panel data from 3,725 primarily poor households in the state of Andhra Pradesh (AP) collected before (2004 and 2006) and after (2008) full MGNREGS phase in matched with administrative project data to estimate household labor supply effects by comparing participants with non-participants. Our identification strategy relies on difference-in-difference (DID) estimation combined with propensity score weighting to counter the non-random selection into the program as well as the well-documented occurrence of work rationing within MGNREGS. The availability of two rounds of pre-intervention data allows us to empirically test for the parallel trends assumption of the DID method.

Our results suggest that participation in the MGNREGS prompted an increase in overall household labor supply by about 12 days only in the summer slack labor season, mostly attributed to adult women. This expansion, though, is not large enough to evade "crowding out" of some labor previously offered to non-MGNREGS labor tasks, particularly private casual labor opportunities, and more so in the main agricultural seasons than the summer slack season. Time spent on paid and unpaid activities, including household chores, do not increase for youth and children in MGNREGS-participating households, suggesting no within-household substitution of labor towards younger members. Our results are drawn from one state where implementation has been applauded and demand levels are relatively high. The findings may nonetheless be relevant to other Indian states and countries considering how to better tailor their cash-for-work programs or labor market interventions.

This paper makes two contributions to the growing literature on labor market effects of public works programs. First, we use household panel data to explore labor supply effects of MGNREGS participation. This distinguishes from most empirical studies, which rely on repeated cross-sectional data to estimate the effects of MGNREGS on labor market outcomes in a general equilibrium framework.[2,3] Imbert and Papp (2015) use district level data and exploit the phased roll out of the program to find a near one-to-one "crowding out" of private sector labor supply due to MGNREGS implementation. Azam (2012) uses the same data and same identification strategy but performs analysis at the individual level to find a positive intent-to-treat impact on labor market participation of females only. Zimmermann (2012) also uses the same data set but a regression discontinuity design which suggests more modest impacts on the labor market. Varshney et al. (2018) too find virtually no crowding out of casual labor supply to agriculture. More recently, Muralidharan et al (2017) use household data to show that a randomly assigned improvement in implementation of the MGNREGS reduced the number of days of unemployment by 13 percent and might have increased employment to both the private sector and to the MGNREGS itself as well as wages overall. Similar results have been reported for workfare programs in Colombia (Alik-Lagrange et al. 2017) and in Ethiopia where the workfare program was bundled with a health insurance program (Shigute et al. 2017) and others across the developing world (Gehrke and

[2] The studies listed here are in addition to several theoretical pieces on labor market effects described by Basu, Chau, Kanbur (2009); Basu (2013); Mukherjee and Sinha (2013); and others.
[3] In experimental data, rather than the observational data that are the only means to study MGNREGS, ours would be a study of treatment effects on the treated, while the prior literature has relied on intent to treat style estimates.

Hartwig 2015). Gehrke (2015) uses a panel dataset and finds that exposure to higher intensity of MGNREGS has the effect of increasing private employment mainly on account of the productive assets created. Agarwal et al. (2017) use firm level panel data to suggest that MGNREGS reduced permanent workers in organized enterprises. While important to our understanding of the country-level impacts of MGNREGS, especially in its inception years, barring a few exceptions, these papers are unable to discern the labor market effects of actual MGNREGS participation by households due to data constraints and the research methods chosen. Partial equilibrium questions, on the other hand, are potentially more salient in a self-selection context and where participation rationing is known to be widespread, with both factors highly relevant to MGNREGS.

Second, our paper also adds to the literature by examining the disaggregate effects of MGNREGS by gender and age group of the household member, specific paid and unpaid work types, and agricultural season. The existing literature pays scant attention to disaggregated labor supply effects. Islam and Sivasankaran (2014) use data from three states to find that younger children spend more time in school while older children spend more time working outside of the household when MGNREGS is operating in their district, implying a reduction in child labor on account of MGNREGS. They show the importance of considering a range of time allocation effects separated by age group, but still are only able to estimate intent-to-treat effects and do not consider actual program participation. We also know that education outcomes for children in MGNREGS participating households have opposite effects depending on whether it is the mother or father who participates in the program (Afridi, Mukhopadhyay, Sahoo 2016). Maity (2020), Li and Sekhri (2020) and Das and Mukherjee (2019) find diverse and nuanced effects on human capital of children, consequent to adult participation in the MGNREGS. These findings encourage a more careful assessment of the overall effects of MGNREGS participation on how children and youth spend their time.

2. Background: MGNREGS and household labor options

MGNREGS follows from the Mahatma Gandhi National Rural Employment Guarantee Act (hereafter, MGNREGA) passed in 2005 granting rural citizens the “right to work” on local and small-scale infrastructure projects (land improvement and clearing for community use, road and agricultural waterway creation, etc.) at a set wage. The legal entitlement that necessitates

MGNREGS makes it the only government employment program like it in the world. Individuals self-target into the program at the village level where projects are determined before seeking funding approval at higher levels of the MGNREGS bureaucracy. While MGNREGS is a national program, it is implemented by individual states and relies heavily on more local level government (districts, sub-districts, and villages) to ensure that the program proceeds as "demand driven". Program benefits were phased in over three sets of districts based on an algorithm ranking poverty, or "backwardness," level.[4] The first phase districts were identified as the poorest and gained access to funds in the 2006/07 fiscal year, the second phase in 2007/08, and the third phase in 2008/09.

In rural India, most households derive their income from a variety of sources, including but not limited to private employment, casual labor, and home-based farming or enterprise development. Trends in employment suggest that off-farm sources of income have expanded relative to agriculture, especially from construction; agriculture, however, continues to be a source of income for a majority of rural households (e.g., Reddy *et al.* 2014; Chand and Srivastava 2014). During the last three decades, the participation rate for males in the rural labor force remained steady at about 56 percent while the rate for females declined from about 33-34 percent in 2004-05 to 26.5 percent by 2009-10. Bonded labor and child labor have declined rapidly, while seasonal migration remains an important component of household livelihood strategies (Deb *et al.* 2014). Typically, labor in India is classified as either permanent or casual/temporary, where permanent workers are considered "attached" to a landlord and spend most (if not all) of their time on this one activity whereas casual/temporary workers move between employers with much greater frequency. MGNREGS offers an additional income-generating means for rural laborers to consider adding to their overall household labor supply portfolio. How MGNREGS participating households account for this new income source – by either adding on top of existing labor days or displacing time spent on other tasks – has the potential to change the very nature of rural labor markets.

While MGNREGS is exclusively offered to adults (age 18 and older), participation by an adult household member may have consequences for the time allocation of younger household members. The income effect of adult MGNREGS participation could reduce youth and children's household and work responsibilities. On the other hand, adult participation could newly burden

[4] Zimmermann (2012) describes this algorithm and ranking process, both in theory and in practice, in more detail.

household youth and children with tasks, like household work or own farm maintenance, to compensate for the absence of one or both parents. Both effects were uncovered for specific sub-populations in analysis of Ethiopia's Productive Safety Net Program, which also offers public sector work opportunities only to adults (Hoddinott, Gilligan, Taffesse 2009). In India, these effects have been studied in an aggregate general equilibrium context (Islam and Sivasankaran 2014) or more specifically with respect to effects on child schooling (Afridi, Mukhopadhyay, Sahoo 2016); true household time allocation evidence for MGNREGS participating households, however, remains anecdotal at best.

We also expect there to be important seasonal dimensions to the questions we ask. In AP, where there are two main agricultural seasons (*kharif* and *rabi*) and a slack season (summer), seasonality is relevant for a number of reasons.[5] First, there is an implicit scaling down of MGNREGS works in AP during the peak agricultural seasons in order to safeguard the interests of farmers and because "earth works" projects during the rainy season are not possible. Second, as with many other states in India, in many parts of the study area, agriculture is primarily rainfed and therefore very little agricultural work is available in the dry summer season. Third, wages can vary dramatically by season given the changing demand for labor. In particular, off-peak (peak) season wages may be lower (higher) than MGNREGS wages. Given these many disaggregated household questions that follow from our interrogation of gender, age group, task, and season-specific effects, we seek to better understand the relationship between time allocation decisions of individual members with the introduction of MGNREGS.

3. Data

We have compiled several datasets for our analysis. The main dataset comes from three rounds of panel household surveys in the Indian state of Andhra Pradesh. We have also assembled administrative data on individuals' MGNREGS participation, Indian Population Census and Indian Village Amenities Census of 2001, and precipitation data from the Tropical Rainfall

[5] *Kharif* season (usually June to October) marks the rainy season that begins with the onset of the summer monsoon. *Rabi* (usually November to February) is the winter season and summer (usually March to May) is the dry season with very little, if any, rainfall. The relative importance of the two agricultural seasons varies by district.

Measuring Mission at NASA, and linked these latter two data sources to the household panel survey data.

Household survey data. The three-round (2004, 2006, and 2008) household survey was administered under the World Bank's Andhra Pradesh Rural Poverty Reduction Project (APRPRP).[6] APRPRP was designed to reach 560 disadvantaged mandals (sub-districts) in sixteen districts, covering a large portion of AP (World Bank 2012). The external impact evaluation approach, carried out by the Centre for Economic and Social Studies (CESS), from which these data are derived, focused on five of the sixteen districts (Kadapa, Warangal, Nalgonda, Nellore, and Visahakapatnam), broadly representative of the three macro-regions within Andhra Pradesh (Telangana, Rayalaseem, and Coastal).[7] Within these districts, villages were randomly selected to be part of the sample, then households randomly sampled within qualitatively-assigned wealth stratification levels: poorest of the poor, poor, not so poor, and not poor.[8] The number of sampled households is 4,759 in 2004, 4,693 in 2006, and 4,533 in 2008.[9]

The wealth of information collected via these questionnaires allows us to answer various labor supply questions related to MGNREGS participation. Moreover, the timing of data collection allows us to observe two pre-MGNREGS years (2004 and 2006) and one within-MGNREGS year after all three phases of districts had access to the program (2008), as well as the varied effects as observed by districts in each of the three MGNREGS phases. Questionnaires were administered separately to a female and male respondent from each household, with some overlap but mostly separate questions. For example, time allocation questions for each member of the household age 10 and older were asked specifically of males. Village level questionnaires were administered to ascertain information better collected through key informant interviews; some of our important variables are derived from this complementary data set.

Administrative data on MGNREGS participation. During the 2008 data collection, enumerators also recorded the MGNREGS job card number of households that participated in MGNREGS, allowing us to link the household survey data with publicly available and audited

[6] For details on this program and its impacts, see Deininger and Liu (2013a, 2013b). Because nearly all households in our sample are APRPRP beneficiaries, we do not expect the impacts of this program to contaminate our results.
[7] Note that our study relies on data before Andhra Pradesh split into two states in 2014.
[8] See Deininger and Liu (2019) for more details on how each category is defined.
[9] The attrition between 2004 and 2008 was 4.7 percent.

MGNREGS administrative data that provide the exact number of days and specific dates individuals worked on MGNREGS projects. Further, the names of individuals provided in the administrative data allow us to match to our household survey data and identify the gender of the MGNREGS participant.[10] Importantly, the structure of the household survey and detailed administrative data allow us to uncover the seasonal dimensions of MGNREGS.

Of the five districts included in our sample, three gained access to MGNREGS in 2006, one in 2007, and one in 2008. For the three agricultural seasons captured in the household survey, households in phase one and two districts are eligible for MGNREGS in the *kharif* and *rabi* seasons covered in the 2008 survey while the phase three districts gain access to MGNREGS starting only in the summer season (during which the 2008 fiscal year begins). When matching the household survey data with the administrative data, we find that 116 households participated in a MGNREGS project during the summer season captured in the 2006 survey. We drop these households from our data set in order to credibly produce uncontaminated estimates given that we use 2006 as our baseline.[11] Due to the nature of the APRPRP beneficiaries, relatively poorer households are oversampled. This skewness works in our favor since MGNREGS participants are also expected to be at the lowest end of the income distribution.[12] After dropping the attrited observations and observations with important missing values, our final data set includes a balanced panel of 3,725 households in the five districts comprising 448 revenue villages within AP.[13]

Table 1 reports the percent of surveyed households who worked on MGNREGS in 2008, by season and MGNREGS phase. Since exact start and end dates for employment on a MGNREGS project are provided in the administrative data, we assign the exact number of days worked to the agricultural seasons that match our household survey data. This table displays not only household

---

[10] Of the full set of households that provided job card information, only 14 were not able to match with the administrative data. These households are dropped from our sample. We have confidence in the MGNREGS administrative data (available at http://nrega.ap.gov.in/) for three reasons: (1) the routine verification via social audits. (2) the results from an author-conducted data verification exercise in select AP villages in 2014. In the latter, household responses to recall questions about MGNREGS wages, number of days worked, and types of assets created matched entries in post-office or bank books where available. (3) Muralidharan, Niehaus, and Sukhtankar (2016) compared MGNREGS payments from their household survey data with those from the administrative data in AP and did not find any project leakages based on household-reported job card numbers.
[11] This represents 4.7 percent of the total household level sample before dropping.
[12] However, without the ability to weight the sample based on the original stratification methodology, this means our data are not necessarily representative of the population of households in the revenue villages or districts sampled. Those were not, however, statistically representative of AP state anyway.
[13] The attrition rate was 3.1 percent from 2004 to 2006 and 3.4 percent from 2006 to 2008.

level participation, but participation by gender and also the incidence of households with both female and male MGNREGS workers. In summer 2008, about 25 percent of our sampled households participated in MGNREGS, the highest of any season. When looking across all three seasons included in the 2008 survey, we find that about 31 percent of households worked on MGNREGS at some point (not shown), similar to the 35 percent Liu and Barrett (2013) calculate for the 2009 fiscal year using the NSS data for all of AP. In most cases, the percentage of households with a female MGNREGS participant is slightly higher than the households with a male participant. Nearly half of all MGNREGS participating households have both a female and male dedicating time to the program in a given season. Table 2 provides the unconditional (including zeros) average number of days worked on MGNREGS by season, with the largest value (about 6) in summer. When restricting to only participants, the average number of days is about 23 in *kharif*, 19 in *rabi*, and 23 in summer (Table 1).

Non-MGNREGS labor supply. The household survey contains a full module on individual household member labor time allocation by agricultural season over the last full year for any household member age 10 and older. Labor days are aggregated into five categories: (1) casual labor, (2) salaried labor, (3) non-farm self-employment, (4) own-farm labor, and (5) household chores.[14] In all labor categories, the number of days worked are recorded. In some sub-categories, the hours worked per day are also observed, in which case we standardize based on an eight hour work day.[15] We match the MGNREGS administrative data with the household survey data to "net out" the private and public sector casual labor by season, household, and gender within household. One day of work under any task is treated as equivalent to one day of work under another.

Table 2 shows the average number of days worked per household in more aggregated labor categories: paid non-MGNREGS labor includes private casual labor, salaried labor, and non-farm self-employment while unpaid non-MGNREGS labor includes own farm labor and household chores. Across seasons and years, days spent on paid non-MGNREGS work dominate those devoted to unpaid non-MGNREGS work. The introduction of MGNREGS in 2008 does not result in a large increase in total days worked between 2006 and 2008. Indeed, the average falls slightly

[14] The one category of labor observed in the survey instrument that we purposefully exclude is the "other" category because it includes, by definition, time spent unemployed.
[15] Standardizing to the number of days worked instead of number of hours worked is preferred since most labor categories in the survey only provide days and many assumptions would be necessary to convert to hours. Moreover, MGNREGS work is observed in days, allowing for more direct comparison.

in *kharif* and increases only marginally in *rabi* and summer. The percentage of households supplying labor to each minor category can be found in Table A1 of the appendix for the full household, Table A2 for household females by age group, and Table A3 for household males by age group. Private casual labor is clearly the type of paid work from which most households derive their income, followed by non-farm self-employment, then salaried labor. Reported youth (age 14-17) and child (age 10-13) labor is miniscule. 2-5 percent of households report female or male youth casual labor.

Other data. In terms of other important external data, rainfall values are derived from geospatial datasets (from the Tropical Rainfall Measuring Mission at NASA) linked to the revenue village boundaries in our study area. We also match village level characteristics as observed before the start of MGNREGS from the Indian Population Census and Indian Village Amenities Census, both administered in 2001.

4. Estimation strategy

In this section, we discuss the econometric models and identification strategies employed to estimate the aggregate and task-specific time allocation effects of MGNREGS-participating households and the number of days worked on MGNREGS projects.

4.1. ATET of MGNREGS participation

Our first objective is to estimate the various household labor supply effects resulting from any (binary) MGNREGS participation, what in experimental data one would call the average treatment effects on the treated (ATET). To do this, we estimate a model of labor supply for household j in revenue village v and district d during survey year t as follows:

$$\boldsymbol{L}_{\boldsymbol{jvdt}} = \alpha_1 \boldsymbol{m}_{jvdt} + \alpha_2 \boldsymbol{x}_{\boldsymbol{jvdt}} + \boldsymbol{\varphi}_{dt} + \boldsymbol{\alpha}_{jvd} + \varepsilon_{jvdt} \tag{1}$$

where $\boldsymbol{L}_{\boldsymbol{jvdt}}$ represents a vector of labor and task outcome variables, including total household labor, paid and unpaid non-MGNREGS labor, labor time split by sub-category (private casual labor, salaried labor, non-farm self-employment, own-farm, and household chores), female and male labor, and labor split between age groups within the household (adults age 18 and older, youth age 14-17, and children age 10-13). $\boldsymbol{m}_{jvdt}$ is a binary MGNREGS treatment variable indicating whether a household participated in the scheme between *t-1* and *t*, $\boldsymbol{x}_{jvdt}$ is a vector of household and village characteristics, $\boldsymbol{\varphi}_{dt}$ is district-year fixed effects which control for time-variant effects of policy changes and demand and supply shocks at the district level including MGNREGS' rollout schedule, $\boldsymbol{\alpha}_{jvd}$ captures time invariant household fixed effects, and ε_{jvdt} is the error term.

To eliminate household fixed effects and to control for the initial conditions that may interact with the subsequent changes in the outcomes, we rely on the 2008 and 2006 survey years to estimate a first difference (FD) version of equation (1) as follows:

$$\Delta \boldsymbol{L}_{jvd,\mathbf{2008}} = \alpha_1 \boldsymbol{m}_{jvd} + \alpha_2 \Delta \boldsymbol{x}_{jvd,\mathbf{2008}} + \boldsymbol{z}_{jvd,\mathbf{2006}} + \boldsymbol{\varphi}_{\boldsymbol{d}} + u_{jvd,2008} \tag{2}$$

where $\Delta \boldsymbol{L}_{jvd,\mathbf{2008}} = \boldsymbol{L}_{jvd,\mathbf{2008}} - \boldsymbol{L}_{jvd,\mathbf{2006}}$, is the FD of the dependent variable, $\Delta \boldsymbol{x}_{jvd,\mathbf{2008}}$ is the FD of the time-variant explanatory variables. $\boldsymbol{z}_{jvd,\mathbf{2006}}$ are time-invariant conditions described in the 2006 data, $\boldsymbol{\varphi}_{\boldsymbol{d}}$ is district fixed effects. The parameter of interest is α_1, which estimates the labor supply effects of MGNREGS participation.

The causal interpretation of α_1 can be undermined by households' self-selection into MGNREGS based on time-variant unobservable characteristics. In a perfect MGNREGS-implementation environment, the "right to work" nature of the program should imply that the decision to participate in MGNREGS, $\boldsymbol{m}$, would be subject to rampant selection effects. In practice, however, it is well-documented that MGNREGS work is rationed through a number of direct and indirect avenues which may occur for any number of administrative or political reasons (Narayanan and Das 2014; Das 2015).

The first is denial of job application, although there is little evidence of rationing in AP. Second, after securing a job, an individual may not be able to access work, either through inadequate jobs and days available given the number of projects in progress, or because the skill, strength, or stamina needed for the work is too great, or the distant location of the work sites ration less skilled or healthy or more remotely located individuals. Liu and Barrett (2013) find that 44 percent of households sought but could not obtain a MGNREGS job nationwide in 2009-10, 25 percent in AP specifically. Ravi and Engler (2015) estimate rationing rates (i.e., demanded a job but not offered one) of 43 percent in 2007 and 21 percent in 2009 for Medak district in AP. Himanshu, Mukhopadhyay, and Sharan (2015) show how job card holders passively wait for work days to be offered by *sarpanches* in Rajasthan. This "supply driven" approach to work availability is similar to reports from AP (Maiorano 2014; Sheahan *et al.* 2016). Third, rationing may occur through the tacit repression of demand. Individuals who may otherwise wish to participate may be discouraged from expressing demand on account of delayed wage payments, participant intimidation, and general frustrations with program administration. For example, Narayanan *et al.* (2017) show that disappointment with implementation leads to "worker discouragement" and the reduced probability of seeking MGNREGS work.[16]

We expect that this well-documented rationing severely dampens self-selection, likely reducing but not eliminating prospective selection bias. We therefore also estimate our DID model using a propensity score weighting (PSW) method proposed by Hirano, Imbens, and Ridder (2003) that seeks to balance participants and non-participants. This involves using a logit model to predict the treatment variable, then using the predictions to calculate weights for application in the DID estimates.[17] We follow the sample trimming method proposed by Crump *et al.* (2006, see Theorem 5.3), as employed by others using these same data (Deininger and Liu 2013a). In our logit models, we include all initial values of the control variables in equation (2) as well as the lagged labor outcome variable (Chen, Mu, Ravallion 2009; Jalan and Ravallion 1998; Mu and Van De Walle 2011), necessitating a unique weight for each model specification (see Table A5 in the Appendix). This method provides "double robustness" results in that if the main model is mis-specified but the selection function is correctly specified, the estimates based on the reweighted regression are still consistent (Wooldridge 2007). DID estimation can also suffer from over-stated standard errors when serial correlation is pronounced (Bertrand, Duflo, Mullainathan 2004). However, the very limited time scale over which our panel data are observed and the fact that our differences

[16] Barriers to MGNREGS participation may be most significant for women. Holmes, Sadana, and Rath (2011) found that women in Madhya Pradesh remain subject to entrenched social norms about what type of work is acceptable and received fewer MGNREGS work days as a result. This unequal access to work is further exacerbated for single women – never-married, divorced, separated, and widowed – who are expected to work alongside a man or are denied job cards because administrators inaccurately claim they do not constitute "a household" (Bhatty 2008).

[17] For participating households, the weight is equal to one; for non-participating households, the weight is equivalent to $\widehat{ps}/(1-\widehat{ps})$ where $\widehat{ps}$ is the predicted propensity score.

essentially fall into a two pre- and post- MGNREGS intervention periods renders this common critique inconsequential in our case.

The DID estimator offers the opportunity to explore unbiased causal relationships by controlling for time invariant unobservable characteristics of households, conditional on the acceptance of the parallel trend assumption, the assumption that subsequent changes in the dependent variable would have been the same for the participating and non-participating groups in the absence of MGNREGS work opportunities. We test the parallel trend assumption using the data from the 2006 and 2004 rounds, when MGNREGS was not available to the households. That is, we test whether MGNREGS participating households as observed in 2008 experienced a common trend in labor supply changes between 2006 and 2008 as they did between 2004 and 2006 when MGNREGS was not an option.

All variables included in $\boldsymbol{x}$ and $\boldsymbol{z}$ for both our DID and DID-PSW estimation are described in more detail in section 4.3. All standard errors are clustered at the revenue village level to limit the effects of potential heteroskedasticity and correlation across nearby observations.

4.2. "Crowding in/out" of time to other tasks on account of time spent on MGNREGS

In addition to the ATET effects of MGNREGS participation, we also test whether one day of MGNREGS participation by a household member influences the time spent on particular income generating activities or household tasks by any household member, i.e., if there are inter-individual, intra-household labor reallocation effects. We adapt from Datt and Ravallion (1994) as well as Imbert and Papp (2015) to specify the following model:

$$\boldsymbol{L_{jvdt}} = \beta_1 \boldsymbol{d}_{jvdt} + \beta_2 \boldsymbol{x_{jvdt}} + \rho_{dt} + \beta_{jvd} + \epsilon_{jvdt} \tag{3}$$

where $\boldsymbol{d}_{jvdt}$ describes the number of days the household spent working on MGNREGS, ρ_{dt} are district-year fixed effects, β_{jvd} are household fixed effects, ϵ_{jvdt} is the error term, and $\boldsymbol{L_{jvdt}}$ and $\boldsymbol{x_{jvdt}}$ are the same vectors as defined in equation (1).

Our parameter of interest is β_1 which estimates the change in time spent on other work on account of one day spent on MGNREGS. If $\beta_1 < 0$, then MGNREGS labor "crowds out" time spent on other activities; if $\beta_1 > 0$, then MGNREGS labor "crowds in" labor for that activity or period. Based on others' findings we expect to observe "crowd out" effects on private labor time (Imbert and Papp 2015) and time spent on farm (Islam and Sivasankaran 2014), although some studies suggest that private labor time in fact increases in areas where the NREGS is implemented well (Muralidharan, 2017; Gehrke, 2015).

Similar to the ATET estimation, we implement a first difference transformation to estimate the following equation using data from the 2006 and 2008 rounds:

$$\Delta \boldsymbol{L}_{\boldsymbol{jvd},\mathbf{2008}} = \beta_1 \boldsymbol{d}_{jvd,2008} + \beta_2 \Delta \boldsymbol{x}_{\boldsymbol{jvd},\mathbf{2008}} + \beta_3 \boldsymbol{z}_{\boldsymbol{jvd},\mathbf{2006}} + \rho_d + u_{jvdt} \tag{4}$$

where $\boldsymbol{z}_{\boldsymbol{jvd},\mathbf{2006}}$ includes the same variables as in equations (2).[18]

Like the ATET estimates, β_1 may not be estimated consistently if endogeneity is a concern. In an ideal implementation world, the number of days devoted to MGNREGS work would be jointly determined with the number of days allocated to any other type of work, leading to simultaneity issues in addition to the inherent program selection effects. Again, as in Section 4.1, we argue that rationing – i.e., not being able to work the number of days one would like, even with a job card in hand – diminishes the worry of endogeneity, although it does not extinguish selection bias entirely.

To the extent that simultaneity and selection still matter beyond the known rationing and in the absence of any convincing instrumental variables (IVs),[19] we conduct a falsification test using the 2004 and 2006 data and the specification in equation (3) in which we use MGNREGS days in 2008, $\boldsymbol{d}_{jvd,2008}$, as the hypothetical MGNREGS days in 2006. If $\boldsymbol{d}_{jvd,2008}$ is correlated with time-variant unobservables that affect the subsequent changes in labor supply and such unobservables are correlated over time, we would expect a statistically significant association with the hypothetical MGNREGS days in the falsification test.

[18] We note that the number of MGNREGS days in 2006 is zero for all households so $\boldsymbol{d}_{jvd,2008} = \Delta \boldsymbol{d}_{jvd,2008}$.

[19] In analysis by Afridi, Mukhopadhyay, and Sahoo (2016), MGNREGS participation is instrumented with rainfall shock in May-June and the number of projects in progress, both at the mandal level. When specifying these variables at the village level instead, neither of these variables – in addition to a host of many others attempted – prove to be good IVs (while relevant using the F-value>10 "rule of thumb," the standard errors are massive when using as IVs).

4.3 Selection of control variables

Household characteristics. We include a range of household characteristics as controls, with summary statistics in Table A4 of the appendix. The choice of which characteristics to include is motivated by similar work by Datt and Ravallion (1994) and analysis using the same AP data set by Deininger and Liu (2019). The first set of these variables are time invariant: (i) the poverty status of the household as classified by the stratification procedures used before household data collection and (ii) household caste. These variables are inserted as linear terms, $\boldsymbol{z}$, not differences, in all of our regressions. The second set of household characteristics is time variant and, therefore, included in $\boldsymbol{x}$, as differences between survey waves. These include a range of household composition variables, gender of the household head, literacy of household members, land ownership and irrigation characteristics, shocks experienced by the household recently, and membership with the APRPRP self-help group.

Village characteristics. Village level control variables are also descriptively explored in Table A4 of the appendix. Most of the village level variables we include can be interpreted as baseline characteristics observed before the introduction of MGNREGS, as derived from the Indian Population Census and Indian Village Amenities Census of 2001. Here we specify variables that seek to describe the population of the village in terms of caste, literacy, and primary occupation as well as the status of available amenities including roads, medical facilities, and agricultural credit societies. Because these variables are observed as static to us, we include them in $\boldsymbol{z}$, as linear (non-differenced) terms in our regressions.

The two important time variant village characteristics we observe are rainfall and wages which are included in $\boldsymbol{x}$. We include village level contemporaneous rainfall levels to control for weather-induced labor market shocks.[20] The casual daily wage rates come directly from the village survey that accompanies the household surveys. Members of the community are asked to recall casual wages separately for females and males in the village split by "peak" and "lean" agricultural seasons over the last year. We apply the "peak" wages to the *kharif* and *rabi* seasons and the "lean"

[20] The rainfall level is a proxy for exogenous demand for work of various types – casual agricultural labor, own farm labor, etc. – in a given season. Kochar (1999) finds that male household members in central India offer more hours to the labor market in the event of *unanticipated* crop shortfalls, not only forecasted ones, even when insurance markets are available. As such, we include the contemporaneous rainfall level in our model.

wages to the summer season. Missing values at the village level are replaced with median values by mandal and, if necessary, by district. Nominal wages are adjusted to real levels using the consumer price index (CPI) specific to rural laborers in AP as released by the Directorate of Economics and Statistics. We deflate by aggregating months across agricultural seasons, setting the summer season observed in the 2008 survey (the most recent season) as the base. We include both the simple average of the adjusted male and female wages as well as a ratio of the male to female wages as control variables. We treat the wage rate as exogenous from the perspective of households at a given point in time since it represents a prevailing community level wage, and shifts in household labor supply will not have an immediate impact on wage levels.[21]

5. Regression results

5.1. ATET of MGNREGS participation

Table 3 displays the regression results for our DID and DID-PSW estimates of equation (2). Because separate regressions must be run to produce individual weights for each DID-PSW model, we do not display the full set of underlying logit propensity score estimation results. Instead, we show the marginal effects for the logit models in Table A5 of the appendix, where results are in line with expectations.[22] The parallel trend tests for the DID and DID-PSW models can be found in appendix Table A6. Of the 42 labor supply outcomes for the DID-PSM results described in Table 3 (columns 4-6), only 4 (about 10 percent) do not pass the parallel trend assumptions test at the 10 percent significance level, a slight improvement over the DID-only results (columns 1-3) where 5 do not pass. We make note of these cases alongside our results in Table 3 and only discuss the findings in this section where the parallel trends have passed.

[21] Changes in agricultural technology induced by the potential contraction in private labor supply on account of MGNREGS (a link suggested by Bhargava 2014) could lead to changes in labor demand by private landlords and therefore effect labor supply for both MGNREGS participating and non-participating households. We argue that any of these unobserved changes are accounted for in the village level casual wage rate.

[22] Here we note the importance of household, village, and district level characteristics that are both time variant (lagged) and invariant in explaining MGNREGS participation for females and males. When estimating Shapely values to determine which groups of variables contribute most to the R-squared (fit) of one model (female MGNREGS participation in summer season), we find that household invariant characteristics account for 25 percent of the variation, household variant for 23 percent, village invariant for 13 percent, village variant for 6 percent, and district invariant for 33 percent.

The ATET estimates for MGNREGS participation reveal that total household labor supply only increases significantly in the summer slack season, where participation leads to an increase in about 12 days worked for both the DID and DID-PSW models (Table 3). This effect results almost entirely from increases in adult female work; time spent working among adult males is not significantly different in MGNREGS participating households. Importantly, we find no increase in time spent on any work activities by youth or children of either gender in MGNREGS participating households. This suggests that adult participation on MGNREGS does not have the unintended consequence of diverting time away from productive capital formation for youth and children over time to meet other household or enterprise obligations.[23]

Since the average number of days on MGNREGS for participating households is 23 in the summer season, the fact that our ATET estimate falls short of this value suggests that the addition of days worked in the summer is likely displacing some non-MGNREGS labor. Indeed, we find that time spent on paid non-MGNREGS work in the summer does fall on account of program participation. The magnitude of the effect on total non-MGNREGS labor in the summer is nearly identical to effect in the opposite direction for total household labor time in the same season, meaning of those 23 days the average household spends on MGNREGS, about half of it displaced previous time spent on paid non-MGNREGS work and half represents new time spent working. Unpaid non-MGNREGS work – including own-farm activities and other household work – is unaffected.

In the two main agricultural seasons, where we find no statistically significant increase in overall time spent working among MGNREGS participating households, we estimate significant, large negative ATET values for time spent on non-MGNREGS *paid* work: approximately -24 and -20 days in the *kharif* season and -14 and -17 days in the *rabi* season, depending on the method. More specifically, MGNREGS participation leads to a decrease in private casual labor, non-farm self-employment and salaried labor, though the effects are not statistically significant across all seasons and methods. On the other hand, unpaid non-MGNREGS work appear unaffected in either season. The fact that we see no overall increase in labor supply in the main agricultural season to combat these several decreases in other types of paid labor foreshadows the results of our "crowding out" analysis below.

[23] Our data do not allow us to make these same claims for children under age 10 but have no reason to assume the results would be any different.

5.2. Time allocation consequences on account of a day of MGNREGS work

Table 4 provides estimates of time allocation consequences on non-MGNREGS labor days on account of total number of days spent on MGNREGS projects by labor type, season, and gender. This table focuses on total household labor supply (inclusive of anyone above age 10) as well as adult female and male labor. The line numbers listed in parenthesis in the text below are included to help guide readers around Table 4. The results from the falsification tests are summarized in appendix Table A7. Only nine out of the total 72 regressions do not pass the falsification tests at the 10 percent significance level. Because we find no evidence of any ATET effects of MGNREGS participation on youth and child time, we relegate the results of these same regressions to appendix Tables A8 (youth) and A9 (children over 10).

We estimate that a one day increase in the number of MGNREGS days provided by any household member "crowds out" 0.90 days of non-MGNREGS labor in the *kharif* season, 0.85 in the *rabi* season, and 0.52 in the slack summer season (line 1). In the *kharif* and *rabi* seasons, the coefficient estimates of MGNREGS days are not significantly different from one, suggesting an almost one-to-one crowd-out effect on non-MGNREGS work during the two main seasons. In contrast, the crowd-out effect is statistically significantly lower than one in the summer slack season. These results are remarkably similar to the results from the ATET regressions (Table 3).

One day of MGNREGS work by any household adult displaces a marginally higher amount of adult female total non-MGNREGS time (line 9) than male time (line 17) in *kharif* (-0.44 versus -0.37), *rabi* (-0.51 versus -0.25), and summer seasons (-0.25 versus -0.21). We note that females have considerably higher participation in MGNREGS in both extensive and intensive margins (Table 1). Female labor accounts for 61 percent, 63 percent, and 63 percent among the total household MGNREGS days in the *kharif, rabi*, and summer seasons, respectively. After scaling the gender-specific effects based on their corresponding shares of MGNREGS days, our results suggest a nearly one-to-one crowd-out effect in the in the *kharif* and *rabi* seasons for both female and male workers. For the summer season, the crowd-out effects are lower for female than male workers and are less than one for both groups.

Paid non-MGNREGS labor (line 2) decreases in the *kharif* and *rabi* seasons while unpaid non-MGNREGS labor (line 3) decreases only in the summer season and with less magnitude.[24] In line with the total household effects (lines 4-8), most of this displaced time for adult females comes from private casual labor (lines 12), with smaller and less statistically significant effects on salaried labor time (line 13) . For adult males, the displacement mainly comes from salaried labor (line 21). These results suggest that MGNREGS not only reduces the time spent on casual temporary labor opportunities, but also more formal permanent jobs, consistent with the results in Table 3. It may be the case that these individuals do not have full time contracts (or do but are able to shirk on them) and can act as private casual laborers who move between MGNREGS and their other duties at will. Consistent with the total household effects, we find no effects on time devoted to non-farm self-employment (lines 14 and 22), own-farm labor (lines 15 and 23), or household work (lines 16 and 24).

We briefly delve into the time allocation effects on youth (Appendix Table A8) and children over ten (Appendix Table A9). For female youth, there are zero effects. For youth males, we find several instances of tiny "crowd out" (household chores, own-farm) effects, depending on the season. The magnitude of all of these effects are less than 0.1 (absolute value), indeed generally closer to 0.01, implying shifts of less than an hour per eight-hour work day. We find no statistically significant labor allocation effects for either female or male children (over ten).

As with our ATET estimates, it does not appear that youth and children are negatively affected by compensating for adult time lost to household chores or other household enterprise time that adult household members participating in MGNREGS neglect. At the same time, we do not observe an overall significant reduction in youth or child time spent on paid or unpaid household activities when an adult household member garners MGNREGS employment. This may be because so few households report youth and child time spend on these activities. But, for those 10 percent of households where female youth contribute time to household chores and, even more, the 7 percent of households where female children contribute to household work, this result could

[24] Imbert and Papp (2015) estimate a 1.5 percent decrease in private employment across all of India on account of the introduction of MGNREGS, but in a general – not partial – equilibrium sense.

also be viewed negatively. Our data do not allow us to delve more deeply into the related schooling effects.[25]

6. Conclusions

This paper explores how participation in India's massive employment guarantee scheme, MGNREGS, changes overall household labor and time allocated to particular types of paid and unpaid tasks disaggregated by gender, age category, and agricultural season using a panel of households across five districts in Andhra Pradesh. These results imply that employment guarantee schemes affect not only overall labor market indicators, as studied in a general equilibrium framework by several other researchers, but also the complex decision-making process of individuals and households, which may have a second order effect on women's empowerment and childhood schooling outcomes. This underscores the value of such disaggregated analysis when analyzing a government labor market intervention as massive and influential as MGNREGS.

In summary, we find that household MGNREGS participation expands total household labor supply in the summer slack season only, mostly for adult females, but reduces the total number of days spent on paid non-MGNREGS work by several days across all seasons, including and most significantly in the two main agricultural seasons. We uncover no evidence of increase in time spent on paid or unpaid work, including household chores, for youth and children in MGNREGS households relative to non-MGNREGS households, suggesting no within-household substitution of work burdens towards younger members. One day spent on MGNREGS work "crowds out" about one day of paid non-MGNREGS work in two of three seasons and mostly draws from the pool of time previously allocated to private casual labor opportunities, particularly among females.

To date, the seasonal dimensions of labor supply response have been described qualitatively but not incorporated into econometric analysis. Our results suggest that labor seasonality is especially important when rural labor markets are prone to major swings in both supply and demand. Our current analytical approach, however, cannot address whether or how

[25] Our data only allow us to observe youth and children who never attended school or dropped out of school completely or for a short term at any point on their life, nothing specific to the recent past. These cases are only relevant to about 1 percent of households, in both the baseline (2004) and endline (2008) years.

MGNREGS contributes to labor spillovers across agricultural seasons, a worthwhile topic for future research.

This line of research not only adds to the growing body of literature specific to MGNREGS, but also can inform other large-scale labor market interventions under consideration by low- or middle-income agrarian nations. This example from India, made special by the underlying constitutional right to work, helps feed into a larger literature exploring if and how the dispersion of government welfare benefits impact the labor market and household labor supply (e.g., de Brauw *et al.* 2015). Further, it can help to inform a related debate about the trade-off between workfare programs and cash distribution as a means of welfare enhancement for poor households (e.g., Alik-Lagrange and Ravallion 2015).

References

Afridi, F., A. Mukhopadhyay, and S. Sahoo. (2016). Female labor force participation and child education in India: evidence from the National Rural Employment Guarantee Scheme. *IZA Journal of Labor and Development,* 5(7).

Agarwal, S., S. Alok, Y. Chopra, and P.L. Tantri. (2017). Government Employment Guarantee, Labor Supply and Firms' Reaction: Evidence from the Largest Public Workfare Program in the World. *Journal of Financial and Quantitative Analysis*; Indian School of Business.

Alik-Lagrange, A., and M. Ravallion (2015). "Inconsistent policy evaluation: A case study for a large workfare program." NBER Working Paper No. 21041. Cambridge, MA.

Alik-Lagrange, A., O. Attanasio, C. Meghir, S. Polana-Reyes, and M. Vera-Hernandes. (2017). "Work pays: different benefits of a workfare program in Colombia." Mimeo.

Azam, M. (2012). "The Impact of Indian Job Guarantee Scheme on Labor Market Outcomes: Evidence from a Natural Experiment." Discussion Paper series, Forschungsinstitut zur Zukunft der Arbeit, No. 6548, Bonn, Germany.

Basu, A.K. (2013). Impact of rural employment guarantee schemes on seasonal labor markets: optimum compensation and workers' welfare. *Journal of Economic Inequality*, 11: 1-34.

Basu, A.K., N.H. Chau, and R. Kanbur. (2009). A theory of employment guarantees: Contestability, credibility and distributional concerns. *Journal of Public Economics*, 93(3-4), 482–497.

Bertrand, M., E. Duflo, and S. Mullainathan. (2004). How much should we trust difference-in-difference estimates? *Quarterly Journal of Economics*, 119(1), 249–275.

Bhargava, A. K. (2014). "The Impact of India's Rural Employment Guarantee on Demand for Agricultural Technology." IFPRI Discussion Paper 01381. Washington, DC.

Bhatty, K. (2008). Falling through the cracks. *The Hindu.* 16 March 2008.

Chand, R., and S.K. Srivastava. (2014). Changes in the Rural Labor Market and Their Implications for Agriculture. *Economic and Political Weekly*, 49(10): 47-54.

Chen, S., R. Mu, and M. Ravallion. (2009). Are there lasting impacts of aid to poor areas? *Journal of Public Economics*, 93, 512–528.

Crump, R.K., V.J. Hotz, G.W. Imbens, and O. Mitnik. (2006). "Moving the goalposts: Addressing limited overlap in the estimation of average treatment effects by changing the estimand." National Bureau of Economic Research Technical Working Paper No. 330. Cambridge, MA.

Das, S. and D. Mukherjee. (2019). The impact of MGNREGS on child labour and child education: an empirical analysis. *Development in Practice*, 29(3): 384-394.

Das, U. (2015). Rationing and Accuracy of Targeting in India: The Case of the Rural Employment Guarantee Act. *Oxford Development Studies*, 43(3), 361–378.

Datt, G., and M. Ravallion. (1994). Transfer benefits from public-works employment: Evidence for rural India. *Economic Journal*, 104(427), 1346–1369.

de Brauw, A., D.O. Gilligan, J. Hoddinott, and S. Roy. (2015). Bolsa Família and Household Labor Supply. *Economic Development and Cultural Change*, 63(3), 423–457.

Deb, U., N. Nagaraj, R. Kumar, M. Bhattarai, R. Padmaja, P.P. Rao, and C. Bantilan. (2014) "Dynamics of Rural Labor Markets in India: Implications for Inclusive Development," Policy Brief 27, Research Program on Policies, Institutions and Markets, ICRISAT, Patancheru.

Deininger, K., and Y. Liu. (2013a). Economic and Social Impacts of an Innovative Self-Help Group Model in India. *World Development*, 43, 149–163.

Deininger, K., and Y. Liu. (2013b). Evaluating Program Impacts on Mature Self-help Groups in India. *World Bank Economic Review*, 27(2), 272–296.

Deininger, K., and Y. Liu. (2019). Heterogeneous Welfare Impacts of India's National Rural Employment Guarantee Scheme: Evidence from Andhra Pradesh. *World Development*, 117: 98-111.

Gehrke, E. (2015). "Can public works infrastructure affect employment outcomes? Evidence from the NREGS in India." German Development Institute. Discussion Paper No. 9/2015.

Gehrke, E., and R. Hartwig. (2015). "How can public works programmes create sustainable employment?" German Development Institute. Discussion Paper No. 11/2015.

Himanshu, Mukhopadhyay, A., & Sharan, M. R. (2015). NREGS in Rajasthan. *Economic and Political Weekly*, 50(6), 52–60.

Hirano, K., G.W. Imbens, and G. Ridder. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica,* 71(4), 1161–1189.

Hoddinott, J., D.O. Gilligan, and A.S. Taffesse. (2009). "The impact of Ethiopia's Productive Safety Net Program on Schooling and Child Labor." Mimeograph.

Holmes, R., N. Sadana, and S. Rath. (2011). "An opportunity for change? Gender analysis of the Mahatma Gandhi National Rural Employment Guarantee." Overseas Development Institute Policy Briefing No. 53. London, UK.

Imbert, C., and J. Papp. (2015). Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee. *American Economic Journal: Applied Economics*, 7(2), 233–263.

Islam, M., and A. Sivasankaran. (2014). "How does Child Labor respond to changes in Adult Work Opportunities? Evidence from NREGA." Mimeograph.

Jalan, J., and M. Ravallion. (1998). Are there dynamic gains from a poor-area development program? *Journal of Public Economics*, 67, 65–85.

Khera, R. (2011). *The Battle for Employment Guarantee*. Oxford University Press.

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics*, 81(1), 50–61.

Li, T. and S. Sekhri, (2020). The Spillovers of Employment Guarantee Programs on Child Labor and Education. *World Bank Economic Review*, 34(1): 164-178.

Liu, Y., and C.B. Barrett. (2013). Heterogeneous Pro-Poor Targeting in the National Rural Employment Guarantee Scheme, *Economic and Political Weekly*, 48(10): 46-53.

Maiorano, D. (2014). The Politics of the Mahatma Gandhi National Rural Employment Guarantee Act in Andhra Pradesh. *World Development*, 58: 95–105.

Maity, B. (2020). Consumption and Time-Use Effects of India's Employment Guarantee and Women's Participation. *Economic Development and Cultural Change*, 68(4): 1185-1231.

Mu, R., and D. Van De Walle. (2011). Rural Roads and Local Market Development in Rural Roads and Local Market Development in Vietnam. *Journal of Development Studies*, 47(5): 709–734.

Mukherjee, D., and U.B. Sinha. (2013). Understanding NREGA: A simple theory and some facts. In N. Siddharthan & K. Narayanan (Eds.), *Human Capital and Development: The Indian Experience*, (pp. 103–128). India: Springer India.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar, "Building State Capacity: Evidence from Biometric Smartcards in India," American Economic Review 106 (2016): 2895-2929.

Muralidharan, K., Niehaus, P., & Sukhtankar, S. (2017). *General equilibrium effects of (improving) public employment programs: Experimental evidence from India* (No. w23838). National Bureau of Economic Research. (DOI): 10.3386/w23838

Narayanan, S., U. Das, Y. Liu, and C.B. Barrett (2017) "The "Discouraged Worker Effect" in Public Works Programs: Evidence from the MGNREGA in India. *World Development*, 100: 31-44.

Ravi, S., and M. Engler. (2015). Workfare as an Effective Way to Fight Poverty: The Case of India's NREGS. *World Development*, 67: 57–71.

Reddy, D.N., A.A. Reddy, N. Nagaraj, and C. Bantilan. (2014). "Emerging Trends in Rural Employment Structure and Rural Labor Markets in India." Working Paper Series No. 56, ICRISAT Research Program Markets, Institutions and Policies, ICRISAT, Patancheru.

Sakketa, Tekalign Gutu; von Braun, Joachim (2019) : Labor-intensive public works programs in sub-Saharan Africa: Experiences and implications for employment policies, ZEF Working Paper Series, No. 180, University of Bonn, Center for Development Research (ZEF), Bonn

Sheahan, M., Y. Liu, C.B. Barrett, and S. Narayanan, S. (2016). Preferential Resource Spending under an Employment Guarantee: The Political Economy of MGNREGS in Andhra Pradesh. *World Bank Economic Review,* 32(3): 551-569.

Shigute, Z., C. Strupat, F. Burchi, G. Alemu, and A.S. Bedi. (2017). "The Joint Effects of a Health Insurance and a Public Works Scheme in Rural Ethiopia." IZA Discussion Paper No. 10939.

Subbarao, K., del Ninno, C., Andrews,C. and Rodríguez-Alas,C. Public Works as a Safety Net: Design, Evidence, and Implementation, World Bank, Washington, D.C. https://doi.org/10.1596/978-0-8213-8968-3

Varshney, D., D. Goel, and J.V. Meenakshi. (2018). The Impact of MGNREGA on Agricultural Outcomes and the Rural Labour Market: A Matched DID Approach. *Indian Journal of Labour Economics,* 61: 589-621.

Wooldridge, J.M. (2007). Inverse Probability Weighted Estimation for General Missing Data Problems, *Journal of Econometrics*, 141: 1281-1301.

World Bank. (2012). “Implementation completion and results report of the Andhra Pradesh Rural Poverty Reduction Project.” Report No. ICR2297.

Zimmermann, L. (2012). “Labor market impacts of a large-scale public works program: evidence from the Indian Employment Guarantee Scheme.” Discussion Paper series, Forschungsinstitut zur Zukunft der Arbeit, No. 6858, Bonn, Germany.

Table 1: Percent of surveyed households participating in MGNREGS in 2008

MGNREGS Phase	HH Member	Kharif % participating	Kharif Days (mean) if participating	Rabi % participating	Rabi Days (mean) if participating	Summer % participating	Summer Days (mean) if participating
1	Any	26.0	24.2	20.8	20.5	30.1	26.6
	Females	21.1	14.5	18.1	13.5	25.8	17.0
	Males	16.1	9.7	11.4	7.0	19.1	9.6
	Both	11.1		8.8		14.7	
2	Any	15.1	16.7	15.9	13.7	19.2	17.9
	Females	12.0	12.0	10.6	6.8	16.4	11.3
	Males	7.6	4.7	12.3	6.9	12.8	6.6
	Both	4.6		7.0		10.1	
3	Any	-		-		15.7	12.3
	Females	-		-		10.9	6.2
	Males	-		-		11.3	6.1
	Both	-		-		6.5	12.3
Total	Any	18.2	23.0	15.3	19.1	24.8	23.4
	Females	14.7	14.1	12.7	12.1	20.7	14.7
	Males	11.0	8.9	9.1	7.0	16.2	8.7
	Both	7.4		6.5		12.1	

Notes: This table shows the percent of surveyed households with any MGNREGS participation by season in the 2008 survey, accomplished by matching job card details with publicly available MIS data. The "any" rows describe household where any member, regardless of gender, participated. This is the variable of interest in our econometric models. The "female" and "male" rows describe households where a female or a male member, respectively, participated. The "both" rows describe the percent of households where both a female and a male member participated.

Table 2: Number of days households participate to each major category of labor

	Kharif (153 days)			Rabi (120 days)			Summer (92 days)		
	2004	2006	2008	2004	2006	2008	2004	2006	2008
Non-MGNREGS paid	132.1	157.8	151.8	150.8	127.9	124.9	84.4	82.9	89.6
	(92.1)	(118.3)	(115.1)	106.6	(94.8)	(90.9)	(67.3)	(71.4	68.9
Non-MGNREGS unpaid	91.9	134.2	134.6	125.4	95.6	97.8	62.7	65.8	63
	(72.1)	(99.5)	(101.3)	95	(69.3)	(74.9)	(46.4)	44.6	44.6
MGNREGS	0	0	4.2	0	0	2.9	0	0	5.8
	(0)	(0)	(12.9)	0	(0)	(10.3)	(0)	0	16.1
Total	224.1	292.0	290.5	276.2	223.5	225.6	147.1	148.8	158.4
	(107.8)	(143.7)	(143.9)	129.8	(111.3)	(111.5)	(79.1)	82.7	82

Notes: This table shows the average number of days per household dedicated to each major aggregated labor category as aggregated from both household survey responses and publicly available MIS data on MGNREGS participation. The non-MGNREGS paid category is inclusive of private casual labor, salaried and farm servant work time, and non-farm self-employment. Non-MGNREGS unpaid work is inclusive of time spent on own-farm and household chores. Standard deviations are in parentheses.

Table 3: ATET estimate of any household MGNREGS participation (binary) on household labor supply outcomes

Dependent variable (all measured in days)	DID									DID-PSW								
	(1) Kharif			(2) Rabi			(3) Summer			(4) Kharif			(5) Rabi			(6) Summer		
	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig
HH labor, total	-3.0	(6.7)		3.2	(5.6)		11.5	(3.6)	***	-2.3	(7.0)		1.7	(5.5)		11.5	(3.7)	***
HH labor, females age 18+	2.3	(3.8)		5.0	(3.1)	†	11.8	(2.0)	*** †	2.2	(3.7)		4.4	(3.1)		10.8	(2.0)	***
HH labor, females age 14-17	-0.6	(1.4)		0.0	(1.0)		0.0	(0.6)		-0.9	(1.5)		0.3	(1.1)		-0.1	(0.7)	
HH labor, females age 10-13	-0.8	(1.0)		-1.1	(0.7)		0.0	(0.5)		0.4	(1.0)		-0.4	(0.8)		-0.1	(0.5)	
HH labor, males age 18+	-3.8	(3.8)		-0.1	(3.4)		1.9	(2.3)		-2.4	(4.0)		-0.7	(3.4)		3.3	(2.4)	
HH labor, males age 14-17	1.4	(1.2)		0.9	(1.0)		-0.4	(0.7)		0.7	(1.4)		0.3	(1.1)		-0.3	(0.7)	
HH labor, males age 10-13	0.9	(0.7)		-0.1	(0.5)	†	0.3	(0.4)		0.0	(0.7)		-0.3	(0.6)		-0.2	(0.4)	
HH labor from paid non-NREGA work, total	-24	(5.5)	***	-13.7	(4.5)	*** †	-8.1	(3.3)	**	-19.8	(5.7)	***	-16.7	(4.5)	***	-11.6	(3.4)	***
HH labor from private casual labor, total	-17.5	(5.2))	***	-6.4	(4.5)	†	-4.0	(3.0)		-6.3	(5.4)	†	-4.4	(4.5)		-2.7	(3.1)	
HH labor from salaried labor, total	-5.1	(3.4)		-2.2	(2.6)		-2.8	(1.6)	*	-7.2	(3.5)	**	-5.3	(2.7)	**	-4.4	(1.7)	**
HH labor from non-farm self-employ, total	-1.3	(2.7)		-5.1	(2.1)	**	-1.3	(1.4)		-4.6	(2.5)	*	-6.2	(2.2)	***	-3.8	(1.4)	*** †
HH labor from unpaid non-NREGA work, total	-2.0	(4.2)		-2.1	(3.8)		-3.5	(2.0)	*	-5.4	(4.3)		-0.8	(3.6)		-0.2	(2.1)	†
HH labor from own-farm labor, total	-0.7	(3.4)		-0.9	(3.0)		-2.2	(1.5)		-3.1	(3.4)		-1.2	(2.9)		0.5	(1.6)	†
HH labor from HH work, total	-1.3	(2.4)		-1.1	(2.0)		-1.4	(1.2)		-2.3	(2.6)		0.8	(2.0)		-0.7	(1.3)	

Notes: *** p<0.01, ** p<0.05, * p<0.1. This table contains the output of various specifications of equation (1). Only the ATET estimates for MGNREGS participation are included in the table. Only phase 1 and 2 households are included in the kharif and rabi analysis, while phase 3 households are added to the summer regressions. For a list of control variables, see Table A4 of the appendix. District fixed effects included. All standard errors are clustered at revenue village level. † = does not pass parallel trend tests at the 10% significance level. Parallel trend test results can be found in Table A6 of the appendix.

Table 4: "Crowding out" estimates of other activities on account of days spent on MGNREGS (full household and adult outcome variables)

		Total household MGNREGS labor days								
	Dependent variable (all measured in days)	(1) Kharif			(2) Rabi			(3) Summer		
		coef	se.	sig	coef	se.	sig	coef	se.	sig
1	*Total HH labor from all non-NREGA work*	-0.90	(0.20)	***	-0.85	(0.17)	***	-0.52	(0.08)	***
2	*Total HH labor from paid non-NREGA work*	-0.79	(0.17)	***	-0.86	(0.14)	***	-0.42	(0.07)	***†
3	*Total HH labor from unpaid non-NREGA work*	-0.11	(0.13)		0.01	(0.13)		-0.11	(0.05)	**
4	Total HH labor from private casual labor	-0.58	(0.15)	***	-0.56	(0.15)	***	-0.30	(0.06)	***
5	Total HH labor from salaried labor	-0.20	(0.09)	**	-0.18	(0.08)	**	-0.08	(0.04)	**
6	Total HH labor from non-farm self-employ	-0.01	(0.06)		-0.12	(0.09)		-0.04	(0.04)	†
7	Total HH labor from own-farm labor	-0.04	(0.11)		0.04	(0.10)		-0.06	(0.04)	
8	Total HH labor from HH work	-0.07	(0.08)		-0.03	(0.08)		-0.05	(0.03)	
9	*Adult female labor from all non-NREGA work*	-0.44	(0.11)	***	-0.51	(0.10)	***	-0.25	(0.05)	***
10	*Adult female labor from paid non-NREGA work*	-0.41	(0.09)	***	-0.53	(0.08)	***	-0.23	(0.04)	***†
11	*Adult female labor from unpaid non-NREGA work*	-0.03	(0.07)		0.02	(0.07)		-0.02	(0.03)	
12	Adult female labor from private casual labor	-0.38	(0.08)	***	-0.42	(0.07)	***	-0.19	(0.03)	***
13	Adult female labor from salaried labor	-0.06	(0.03)	*	-0.04	(0.02)	*	-0.02	(0.01)	***
14	Adult female labor from non-farm self-employ	0.03	(0.04)	†	-0.06	(0.04)		-0.01	(0.02)	†
15	Adult female labor from own-farm labor	-0.01	(0.05)		0.05	(0.04)		-0.01	(0.02)	
16	Adult female labor from HH work	-0.02	(0.05)		-0.03	(0.06)		-0.02	(0.03)	
17	*Adult male labor from all non-NREGA work*	-0.37	(0.13)	***	-0.25	(0.12)	**	-0.21	(0.05)	***
18	*Adult male labor from paid non-NREGA work*	-0.32	(0.11)	***	-0.25	(0.10)	**	-0.14	(0.05)	***
19	*Adult male labor from unpaid non-NREGA work*	-0.05	(0.07)		0.00	(0.08)	†	-0.07	(0.03)	**
20	Adult male labor from private casual labor	-0.1	(0.09)		-0.04	(0.10)	†	-0.05	(0.04)	
21	Adult male labor from salaried labor	-0.17	(0.08)	**	-0.16	(0.07)	**	-0.06	(0.03)	*
22	Adult male labor from non-farm self-employ	-0.05	(0.05)		-0.05	(0.07)		-0.03	(0.03)	
23	Adult male labor from own-farm labor	-0.02	(0.06)		0.01	(0.08)	†	-0.04	(0.03)	
24	Adult male labor from HH work	-0.03	(0.03)		-0.01	(0.03)		-0.03	(0.01)	***†

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table contains the regression results for estimating equation (4). Standard errors clustered at the revenue village level. District fixed effects included in all specifications. Only phase 1 and 2 households are included in the kharif and rabi analysis, while phase 3 households are added to the summer regressions. See Table A4 of the appendix for a list of control variables used in all regression. † = does not pass falsification tests at the 10% significance level. Falsification test results can be found in Table A7 of the appendix. Results for youth and children found in Tables A8 and A9 of the appendix, respectively.

APPENDIX

Table A.1: Percent of households with non-zero labor days supplied to each minor category

	Kharif			Rabi			Summer		
	2004	2006	2008	2004	2006	2008	2004	2006	2008
Non-MGNREGS paid work									
Private casual labor	73.6	74.4	74.6	73.0	73.9	73.3	66.3	65.0	71.9
Salaried	15.3	13.8	16.2	15.1	13.5	16.2	14.8	13.3	16.1
Non-farm self-employment	25.2	21.6	18.7	23.9	21.1	18.8	25.3	22.7	19.4
Non-MGNREGS unpaid work									
Own farm	37.1	45.7	44.1	44.0	37.0	38.2	30.2	32.2	30.6
Household chores	98.9	99.0	98.7	98.7	99.0	98.6	98.4	98.8	98.4
MGNREGS	0.0	0.0	18.2	0.0	0.0	15.3	0.0	0.0	24.8

Notes: Casual labor includes all non-MGNREGS agricultural and non-agricultural labor days. Salaried labor includes farm servant labor. Non-farm self-employment includes days spent self-employed and with income-generation related to common property resources. Own farm includes days spent in crop and livestock agriculture at the household's farm. See main text for information on the data sources used to create these aggregates.

Table A.2: Percent of households with non-zero labor days supplied to each minor category for females by age group, season, and year

	Kharif			Rabi			Summer		
	2004	2006	2008	2004	2006	2008	2004	2006	2008
Females (adult: age 18 and older)									
Private casual labor	62.3	63.3	63.9	61.4	63.0	62.4	51.0	51.2	59.7
Salaried labor	2.2	2.7	3.0	2.1	2.4	3.0	2.1	2.1	3.0
Non-farm self-employment	13.4	11.5	9.2	12.6	11.1	9.0	13.6	12.4	9.4
Own farm	27.2	40.3	39.5	37.0	30.1	31.2	18.9	24.2	23.0
Household chores	96.3	96.0	95.4	96.1	96.0	95.0	95.7	95.6	94.4
MGNREGS	0.0	0.0	14.7	0.0	0.0	12.7	0.0	0.0	20.7
Females (youth: age 14 to 17)									
Private casual labor	4.9	3.9	3.1	4.8	4.0	3.0	4.2	3.1	2.9
Salaried labor	0.1	0.1	0.2	0.1	0.0	0.2	0.1	0.0	0.2
Non-farm self-employment	0.7	0.5	0.2	0.6	0.4	0.2	0.6	0.6	0.3
Own farm	1.4	1.9	1.7	2.0	1.3	1.3	1.0	1.1	1.1
Household chores	9.2	9.8	9.4	9.1	9.9	9.3	9.0	9.7	9.4
MGNREGS									
Females (child: age 10 to 13)									
Private casual labor	1.6	1.3	1.0	1.5	1.3	1.0	1.3	1.1	1.0
Salaried labor	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.1	0.0
Non-farm self-employment	0.3	0.3	0.2	0.3	0.4	0.3	0.2	0.3	0.2
Own farm	0.8	0.9	0.7	1.2	0.7	0.5	0.6	0.6	0.4
Household chores	4.7	6.9	7.2	4.6	6.9	7.0	4.6	6.9	7.0
MGNREGS									

Notes: See notes for Table A1.

Table A.3: Percent of households with non-zero labor days supplied to each minor category for males by age group, season, and year

	Kharif			Rabi			Summer		
	2004	2006	2008	2004	2006	2008	2004	2006	2008
Males (adult: age 18 and older)									
Private casual labor	55.3	55.8	53.6	54.6	55.3	52.0	50.0	49.0	52.9
Salaried labor	12.9	11.7	13.4	12.9	11.2	13.4	12.7	11.2	13.2
Non-farm self-employment	20.8	17.0	14.7	19.4	16.3	14.9	20.8	18.0	15.4
Own farm	32.1	41.8	39.7	38.9	33.3	34.1	23.9	27.6	26.1
Household chores	30.3	56.6	54.9	30.0	56.6	54.7	29.9	56.5	54.7
MGNREGS	0.0	0.0	11.0	0.0	0.0	9.1	0.0	0.0	16.2
Males (youth: age 14 to 17)									
Private casual labor	3.1	3.5	3.1	3.1	3.4	3.1	2.9	3.0	3.2
Salaried labor	0.7	0.8	0.8	0.7	0.8	0.8	0.6	0.8	0.9
Non-farm self-employment	0.8	0.4	0.3	0.8	0.6	0.3	0.9	0.6	0.3
Own farm	1.6	2.1	1.4	2.0	1.7	1.1	1.5	1.5	0.9
Household chores	2.5	5.1	5.6	2.6	5.0	5.5	2.6	5.0	5.6
MGNREGS									
Males (child: age 10 to 13)									
Private casual labor	0.6	0.6	0.4	0.5	0.6	0.5	0.3	0.4	0.5
Salaried labor	0.2	0.2	0.1	0.2	0.1	0.2	0.2	0.1	0.1
Non-farm self-employment	0.2	0.2	0.1	0.2	0.2	0.1	0.2	0.1	0.1
Own farm	0.6	0.9	0.6	0.6	0.8	0.4	0.5	0.8	0.4
Household chores	1.4	3.5	3.7	1.4	3.4	3.8	1.4	3.4	3.8
MGNREGS									

Notes: See notes for Table A1.

Table A.4: Summary statistics of control variables

Variable	Mean	SD	25th	50th	75th
Household classified as "poorest of the poor" (=1)	0.4	0.5	0.0	0.0	1.0
Household classified as "poor" (=1)	0.3	0.5	0.0	0.0	1.0
Household classified as "not so poor" (=1)	0.2	0.4	0.0	0.0	0.0
Household classified as "not poor" (=1)	0.1	0.3	0.0	0.0	0.0
Household in scheduled caste (SC) (=1)	0.2	0.4	0.0	0.0	0.0
Household in scheduled tribe (ST) (=1)	0.2	0.4	0.0	0.0	0.0
Household in backward caste (BC) (=1)	0.4	0.5	0.0	0.0	1.0
Household in other caste (OC) (=1)	0.2	0.4	0.0	0.0	0.0
Households has at least one member who can write (=1)	0.8	0.4	1.0	1.0	1.0
Female headed households (=1)	0.1	0.3	0.0	0.0	0.0
Number of female adults in household	1.4	0.6	1.0	1.0	2.0
Number of male adults in household	1.4	0.8	1.0	1.0	2.0
Households has both a male and female adult (=1)	0.9	0.3	1.0	1.0	1.0
Number of household members age 10-13 (children)	0.4	0.6	0.0	0.0	1.0
Number of household members age 14-17 (children)	0.3	0.6	0.0	0.0	1.0
Household size	4.1	1.7	3.0	4.0	5.0
Household size – squared	19.3	16.4	9.0	16.0	25.0
Household dependency ratio (0-100)	54.1	57.7	0.0	40.0	100.0
Households with no member age 15-64 (=1)	0.0	0.2	0.0	0.0	0.0
Number of acres owned and irrigated by household	0.6	1.5	0.0	0.0	0.5
Number of acres owned and rainfed by household	0.9	2.1	0.0	0.0	1.0
Number of acres owned by household – squared	9.2	37.0	0.0	0.3	4.0
Number of shocks (0-12) experienced by the household recently	0.5	0.7	0.0	0.0	1.0
Household is part of a self-help group (=1)	0.4	0.5	0	0	1
Wage gap: hh casual wage in 2006 – village avg NREGA wage in 2008*	-16.7	46.0	-40.3	-27.0	-8.7
Access to medical facility in village (=1)	0.7	0.5	0.0	1.0	1.0
Number of agricultural credit societies in village	0.2	0.4	0.0	0.0	0.0
Paved approach road to village (=1)	0.8	0.4	1.0	1.0	1.0
Distance to nearest town from village (km)	40.8	26.9	18.0	35.0	63.0
Population density (households per hectare) in village	0.7	0.9	0.3	0.5	0.7
Percent of village population that is SC/ST	32.8	24.4	17.0	26.4	41.6
Percent of village population that is illiterate	54.3	10.0	48.0	54.2	61.0
Percent of village population that is a cultivator	15.7	10.1	9.2	14.0	20.0
Percent of village population that is an agricultural laborer	15.3	10.6	7.1	14.0	21.9
Percent of village population that is a marginal worker	12.4	10.8	4.0	9.5	18.2
Percent of village population that does not work	47.2	7.7	42.1	46.3	51.5
Average rainfall rate (mm/hr) across months in season	0.1	0.1	0.0	0.1	0.2
Average rainfall rate (mm/hr) across months in season - squared	0.0	0.0	0.0	0.0	0.0
Village level daily wage rate for casual labor (male and female avg)	66.7	23.8	48.1	60.1	82.1
Ratio of village level daily wage for men and women casual laborers	1.7	0.4	1.4	1.7	2.0

Notes: These statistics are calculated with data from all three survey years. Number of households in balanced panel = 3,725. *This variable is only used in the propensity score weighting logit regressions. The wage gap is computed using the household-specific wages in 2006 (from household survey data) and the MGNREGS wages in 2008 (from publicly available MGNREGS administrative data).

Table A.5: Marginal effects of logit models describing determinants of MGNREGS participation in 2008 by season of participant using lagged (2006) characteristics

	Kharif	Rabi	Summer
HH is poorest of the poor =1	0.459*	0.457*	0.623***
	(0.240)	(0.247)	(0.197)
HH is poor =1	0.526**	0.579**	0.696***
	(0.228)	(0.231)	(0.194)
HH is not so poor =1	0.310	0.123	0.251
	(0.228)	(0.223)	(0.184)
HH is SC caste =1	0.530***	0.318**	0.275**
	(0.124)	(0.143)	(0.119)
HH is ST caste =1	-0.381	-0.439*	-0.0784
	(0.244)	(0.224)	(0.179)
HH is OC =1	-0.518***	-0.382**	-0.236*
	(0.178)	(0.190)	(0.143)
Medical facility in vil =1	-0.183	0.106	-0.209
	(0.166)	(0.189)	(0.154)
No. ag credit societ. in vil =1	-0.111	-0.453**	-0.206
	(0.144)	(0.188)	(0.152)
Paved road to vil =1	0.190	0.268	0.0675
	(0.202)	(0.237)	(0.184)
Dist. from vil to town (km)	-0.00320	-0.00295	0.00466
	(0.00366)	(0.00416)	(0.00317)
No. hh per ha in vil	-0.344*	-0.218	-0.224*
	(0.190)	(0.178)	(0.116)
Percent SC/ST in vil	0.00297	0.00821	0.00467
	(0.00512)	(0.00583)	(0.00368)
Percent illiterate in vil	-0.00706	-0.00523	-0.00992
	(0.00902)	(0.00982)	(0.00892)
Percent cultivators in vil	0.00746	0.0160	0.0137
	(0.0142)	(0.0155)	(0.0121)
Percent ag laborers in vil	0.0236	0.00605	0.00761
	(0.0145)	(0.0163)	(0.0133)
Percent marginal worker in vil	0.0150	0.0127	0.0154
	(0.0140)	(0.0151)	(0.0123)
Percent non-workers in vil	-0.00247	-0.00742	0.00487
	(0.0185)	(0.0212)	(0.0180)
>0 HH mem can write =1	0.167	0.0850	0.150
	(0.131)	(0.145)	(0.114)
Female headed HH =1	-0.255	-0.0754	-0.00122
	(0.219)	(0.253)	(0.165)
No. female adults in HH	-0.164	0.0273	-0.0624
	(0.112)	(0.126)	(0.0987)
No. male adults in HH	-0.0514	0.0822	0.0191
	(0.106)	(0.110)	(0.0861)
Male and female adult =1	0.701**	0.586**	0.452**
	(0.278)	(0.295)	(0.203)
No. members age 10-13	-0.0448	0.107	-0.0738
	(0.0921)	(0.0947)	(0.0848)
No. members age 14-17	-0.0467	0.210**	0.178**
	(0.0957)	(0.102)	(0.0819)
Household size	0.0366	0.0122	-0.00609
	(0.0496)	(0.0544)	(0.0403)
Household size - sq	0.00248	-0.00784	-0.00270

	(0.00633)	(0.00697)	(0.00510)
Household size	0.000207	0.000989	0.00158*
	(0.00118)	(0.00114)	(0.000946)
HH depend. ratio is zero =1	-1.461***	-1.495**	-1.583***
	(0.527)	(0.587)	(0.462)
No. HH acres own and irrig.	-0.00286	0.0839	-0.00448
	(0.0583)	(0.0641)	(0.0484)
No. HH acres own and rainfed	0.0351	0.129**	0.0214
	(0.0516)	(0.0559)	(0.0433)
No. acres owned by HH - sq	-0.00534	-0.0110**	-0.00156
	(0.00416)	(0.00490)	(0.00285)
No. of HH shocks	-0.0290	0.183**	0.0792
	(0.0839)	(0.0838)	(0.0673)
HH is in SHG =1	0.294***	0.280**	0.471***
	(0.104)	(0.117)	(0.0913)
HH specific wage gap	-0.00655***	-0.00776***	-0.00514***
	(0.00165)	(0.00203)	(0.00130)
Seasonal rainfall amount	8.952	7.471	-41.35
	(20.56)	(9.074)	(29.13)
Seasonal rainfall amount - sq	-15.89	-0.256	143.6
	(33.64)	(35.14)	(193.1)
Village casual wage rate	0.00441	0.00464	0.0000149
	(0.00544)	(0.00602)	(0.00570)
Ratio of male to female wage	0.0346	-0.00864	-0.284*
	(0.175)	(0.196)	(0.155)
Lagged total HH labor supply	0.000388	0.0000565	-0.0000980
	(0.000441)	(0.000600)	(0.000616)
District fixed effects	Y	Y	Y
Number of households	2,914	2,914	3,725
Pseudo R-squared	0.108	0.083	0.097

Table A.6: Test for parallel trends in outcome variables prior to MGNREGS (any household participation)

Dependent variable (all measured in days)	DID									DID-PSW								
	(1) Kharif			(2) Rabi			(3) Summer			(4) Kharif			(5) Rabi			(6) Summer		
	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig	coef	se.	sig
HH labor, total	1.5	(5.9)		-8.3	(6.0)		-2.3	(3.8)		3.7	(6.1)		-0.2	(5.9)		-0.3	(3.9)	
HH labor, females age 18+	-2.9	(3.6)		-8.2	(3.7)	**	-4.4	(2.2)	*	-0.8	(3.7)		-3.2	(3.5)		-1.3	(2.2)	
HH labor, females age 14-17	1.3	(1.4)		-0.8	(1.3)		-0.4	(0.8)		2.1	(1.5)		0.8	(1.4)		-0.1	(0.8)	
HH labor, females age 10-13	1.6	(1.1)		0.9	(1.1)		0.3	(0.5)		1.1	(1.2)		0.6	(1.1)		-0.2	(0.5)	
HH labor, males age 18+	2.8	(3.4)		-0.8	(3.6)		2.3	(2.2)		3.2	(3.4)		2.7	(3.5)		2.2	(2.4)	
HH labor, males age 14-17	-0.2	(1.2)		0.2	(1.3)		-0.2	(0.8)		-0.2	(1.3)		-0.4	(1.3)		-0.3	(0.8)	
HH labor, males age 10-13	-0.6	(0.7)		1.0	(0.5)	**	0.2	(0.4)		-1.1	(0.7)		0.1	(0.5)		-0.4	(0.4)	
HH labor from paid non-NREGA work	4.2	(5.0)		-9.3	(4.8)	*	-4.4	(3.2)		3.9	(5.2)		-2.2	(5.0)		-4.3	(3.4)	
HH labor from private casual labor	4.2	(4.7)		-13.2	(4.7)	***	-4.0	(3.0)		9.7	(5.1)	*	-0.4	(5.0)		-0.1	(3.2)	
HH labor from salaried labor	1.3	(2.9)		2.5	(2.4)		1.3	(1.6)		0.4	(3.1)		-1.0	(2.5)		0.1	(1.6)	
HH labor from non-farm self-employ	-1.3	(2.5)		1.3	(2.4)		-1.7	(1.5)		-3.5	(2.6)		0.1	(2.5)		-3.6	(1.6)	**
HH labor from unpaid non-NREGA work	-2.8	(4.2)		1	(3.7)		2.1	(2.3)		-0.1	(4.1)		3.1	(3.5)		4.2	(2.2)	*
HH labor from own-farm labor	-1	(3.5)		2.2	(3.1)		2.2	(1.9)		0.2	(3.4)		3.0	(3.0)		3.5	(1.8)	**
HH labor from HH work	-1.8	(2.3)		-1.2	(1.9)		0.0	(1.3)		-0.1	(2.3)		0.1	(1.9)		0.8	(1.3)	

Notes: Related to estimates displayed in Table 3 of the main text. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Falsification test results using outcome variables prior to MGNREGS (2006-2004)

	Dependent variable (all measured in days)	Total household MGNREGS labor days								
		(1) Kharif			(2) Rabi			(3) Summer		
		coef	se.	sig	coef	se.	sig	coef	se.	sig
1	*Total HH labor from all non-NREGA work*	0.08	(0.17)		-0.06	(0.19)		-0.06	(0.09)	
2	*Total HH labor from paid non-NREGA work*	0.08	(0.15)		-0.21	(0.17)		-0.12	(0.07)	*
3	*Total HH labor from unpaid non-NREGA work*	0.00	(0.12)		0.15	(0.11)		0.06	(0.07)	
4	Total HH labor from private casual labor	0.08	(0.15)		-0.33	(0.21)		-0.05	(0.07)	
5	Total HH labor from salaried labor	0.08	(0.07)		0.08	(0.06)		0.02	(0.03)	
6	Total HH labor from non-farm self-employ	-0.08	(0.06)		0.04	(0.13)		-0.09	(0.05)	*
7	Total HH labor from own-farm labor	-0.03	(0.09)		0.12	(0.08)		0.02	(0.05)	
8	Total HH labor from HH work	0.03	(0.06)		0.03	(0.06)		0.04	(0.03)	
9	*Adult female labor from all non-NREGA work*	-0.02	(0.11)		-0.15	(0.13)		-0.11	(0.06)	
10	*Adult female labor from paid non-NREGA work*	0.00	(0.08)		-0.12	(0.10)		-0.08	(0.04)	*
11	*Adult female labor from unpaid non-NREGA work*	-0.02	(0.07)		-0.03	(0.08)		-0.03	(0.05)	
12	Adult female labor from private casual labor	0.09	(0.07)		-0.08	(0.10)		0.01	(0.04)	
13	Adult female labor from salaried labor	0.03	(0.03)		0.00	(0.03)		-0.01	(0.01)	
14	Adult female labor from non-farm self-employ	-0.11	(0.03)	***	-0.04	(0.06)		-0.08	(0.03)	***
15	Adult female labor from own-farm labor	-0.02	(0.05)		-0.02	(0.04)		-0.03	(0.02)	
16	Adult female labor from HH work	0.00	(0.05)		-0.01	(0.06)		0.00	(0.04)	
17	*Adult male labor from all non-NREGA work*	0.12	(0.09)		0.07	(0.10)		0.05	(0.07)	
18	*Adult male labor from paid non-NREGA work*	0.09	(0.09)		-0.1	(0.10)		-0.02	(0.06)	
19	*Adult male labor from unpaid non-NREGA work*	0.03	(0.06)		0.17	(0.08)	**	0.07	(0.04)	
20	Adult male labor from private casual labor	-0.02	(0.09)		-0.25	(0.12)	**	-0.07	(0.06)	
21	Adult male labor from salaried labor	0.07	(0.06)		0.09	(0.06)		0.06	(0.04)	
22	Adult male labor from non-farm self-employ	0.04	(0.05)		0.06	(0.08)		-0.01	(0.04)	
23	Adult male labor from own-farm labor	0.01	(0.06)		0.13	(0.07)	*	0.02	(0.05)	
24	Adult male labor from HH work	0.02	(0.03)		0.04	(0.03)		0.06	(0.02)	***

Notes: Related to estimates displayed in Table 4 of the main text. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: "Crowding out" estimates of other activities on account of days spent on MGNREGS (youth outcome variables)

	Effects on Total household MGNREGS labor days			Falsification Test (2006-2004)		
	Kharif	Rabi	Summer	Kharif	Rabi	Summer
Youth female labor from all work	0.01	-0.03	0.01	-0.04	-0.08	-0.01
Youth female labor from paid work	-0.01	-0.03	0.01	-0.01	-0.05	-0.01
Youth female labor from unpaid work	0.01	0.00	0.00	-0.03	-0.03	0.01
Youth female labor from private casual labor	-0.01	-0.03	0.02	-0.01	-0.05	-0.01
Youth female labor from salaried labor	0.00	0.00	0.00	0.00	0.00	0.00
Youth female labor from non-farm self-employ	-0.01	0.00	0.00	0.01	0.00	0.00
Youth female labor from own-farm labor	0.02	0.00	0.00	-0.02	0.00	0.00
Youth female labor from HH work	0.00	0.00	0.00	-0.01	-0.02	0.00
Youth male labor from all work	0.01	0.04	0.00	0.00	0.01	0.01
Youth male labor from paid work	0.04	0.05	0.01	0.00	0.00	0.00
Youth male labor from unpaid work	-0.02 **	-0.01	-0.01	0.00	0.00	0.00
Youth male labor from private casual labor	0.01	0.02	0.01	0.01	0.02	0.00
Youth male labor from salaried labor	0.03	0.04 ***†	0.01	-0.01	-0.03 **	0.00
Youth male labor from non-farm self-employ	0.00	-0.01	0.00	0.00	0.01	0.00
Youth male labor from own-farm labor	-0.01	0.00	-0.01 *	-0.01	0.00	0.01
Youth male labor from HH work	-0.01 **	-0.01	0.00	0.00	0.00	0.00

Notes: See Table 4 of main text for notes. *** p<0.01, ** p<0.05, * p<0.1. † = does not pass falsification tests at the 10% significance level.

Table A.9: "Crowding out" estimates of other activities on account of days spent on MGNREGS (child outcome variables)

	Effects on Total household MGNREGS labor days						Falsification Test (2006-2004)					
	Kharif		Rabi		Summer		Kharif		Rabi		Summer	
Child female labor from all work	-0.01		0.01		-0.01		0.02		0.05		0.02	
Child female labor from paid work	0.00		0.01		0.00		0.01		0.03		0.00	
Child female labor from unpaid work	-0.01		0.00		0.00	†	0.01		0.02		0.02	**
Child female labor from private casual labor	0.00		0.01		0.00		0.01		0.01		0.00	
Child female labor from salaried labor	0.00		-0.02		0.00		0.00		0.02		0.00	
Child female labor from non-farm self-employ	0.00	†	0.01		0.00	†	-0.01	**	0.00		0.00	**
Child female labor from own-farm labor	-0.02		-0.01		0.00		0.01		0.01		0.01	
Child female labor from HH work	0.00		0.01		0.00	†	0.01		0.01		0.01	**
Child male labor from all work	0.02		-0.01	†	0.00	†	0.00		0.03	*	0.02	*
Child male labor from paid work	0.02		-0.01		0.00		0.00		0.02		0.00	
Child male labor from unpaid work	-0.01		0.00		0.00	†	0.00		0.01		0.01	**
Child male labor from private casual labor	0.01		0.00		0.00		0.00		0.01		0.00	
Child male labor from salaried labor	0.00		-0.01		0.00		0.00		0.00		0.00	
Child male labor from non-farm self-employ	0.01	*†	0.00		0.00		-0.01	*	0.00		0.00	
Child male labor from own-farm labor	0.00		0.00		0.00	†	0.00		0.00		0.01	*
Child male labor from HH work	-0.01		-0.01		0.00		0.00		0.01		0.00	

Notes: See Table 4 of main text for notes. *** p<0.01, ** p<0.05, * p<0.1. † = does not pass falsification tests at the 10% significance level.