Public Sector Job Guarantees and Family Planning Choices in Rural India

Abstract

We exploit the staggered timing of an employment guarantee program in rural India to investigate how providing work opportunities affects married women's use of family planning methods. Using survey data from rural India, we employ a difference-in-differences strategy and inverse probability of treatment weighting to control for confounding factors influencing family planning decisions. Results suggest an increase of 1.8 percentage points (a 3.2% increase from the variable's sample mean) in the use of modern family planning methods among married women after the introduction of an employment guarantee program. This caused a decrease in family members' opposition to contraception. Likely mechanisms for these impacts include reduced unemployment for women compared to men, increased wages paid to women, and the facilitation of out-migration. Results are robust to the choice of controls, regression weights, and matching method. We also demonstrate that program impacts increase with the amount of time a workfare program has been in place. These results provide empirical evidence that employment guarantees that include women can affect family planning choices, with important implications for economic development outcomes.

Keywords: workfare programs, family planning, contraceptive use, India

JEL Codes : I38, J13

1. Introduction

In rural areas of developing countries, family planning has important implications for human capital investments (Miller 2010), labor market decisions (Jensen 2012; Van den Broeck 2020), and economic development outcomes (Canning and Schultz 2012). According to the United Nations (UN), contraceptive prevalence is a key indicator for measuring improvements in reproductive health and is an indicator used to assess progress towards the UN Sustainable Development Goals. Yet, in developing countries, contraceptive use often remains low. For example, in India in 2019, just 67 percent of married women of reproductive age used contraception of any form, compared with 82 percent in the Republic of Korea in 2018 (United-Nations 2022).[1] Explanations for this low use of contraceptives include lack of information about contraceptive methods, barriers to accessing modern contraception (Cleland et al. 2006), women's perception of husband opposition (Ashraf, Field, and Lee 2014), intimate partner violence (McCarthy 2019), women's preference for large families (Gage 1995), income constraints (Palamuleni 2013), and lack of financial autonomy for women (Westeneng and d'Exelle 2015; Van den Broeck 2020).

Van den Broeck (2020) demonstrates that labor market participation, particularly off-farm wage employment for rural women can overcome many factors that limit contraceptive use in developing countries. This occurs because women who work add to total household income while increasing their share of total income. As a result, women experience greater autonomy and improved bargaining power in household decisions related to safe sex and reproduction.

Across the developing world, there are several examples of public workfare programs (e.g., in Ethiopia, Argentina, and Rwanda) that provide employment opportunities and act as

a source of employment and income for the poor. The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) in India is the largest workfare program in the world, with a total expenditure of 696.18 billion Indian rupees (8.5 billion US dollars using 2023 exchange rates) in the 2018-2019 fiscal year (Ministry of Rural Development, Government of India).[2] Importantly, MGNREGA stipulates that women represent at least one-third of beneficiaries and that they are paid wages equal to those of men. Further, women participating in MGNREGA receive wages directly in a personal bank account. Therefore, the creation of job opportunities and income controlled by women has the potential to affect choices about family size and the timing of childbirth while increasing the role of women's preferences in decisions (Jensen 2012; Van den Broeck 2020).

Despite the potential for job programs to influence family planning decisions, this has not been demonstrated empirically. To bridge this gap, we explore the impacts of a government-sponsored job guarantee program on the use of contraception in rural India. We also examine how the program, MGNREGA, impacted women's age at first birth and family attitudes towards contraception. To estimate the impacts of MGNREGA, we use data from the largest demographic and health survey carried out in India, the District Level Household and Facility Survey (DLHS). Following Chari et al. (2019), we exploit the phased roll out of MGNREGA at the district level (similar to a US county) to estimate a difference-in-differences (DiD) model. Because the MGNREGA rollout was targeted rather than random, treatment endogeneity complicates the estimation of causal impacts. We address this challenge by using the inverse probability of treatment weighting technique (Hirano, Imbens, and Ridder 2003). We also explore the impact of the amount of time MGNREGA has been in a given

location, consider an event study specification, and demonstrate robustness to omission of controls, different weighting, and alternative matching methods.

We find that married women in rural districts increased their use of modern methods of family planning after the introduction of MGNREGA by an average of 1.8 percentage points. Women's average age at first birth increases by 0.1 years while opposition to contraception from husbands (and other family members) falls. An additional year of program implementation increases the use of any contraception by 1.2 percentage points. Likely mechanisms for these impacts include reduced unemployment for women compared to men, increased wages paid to women, and the facilitation of out-migration (Merfeld 2019). We find empirical evidence that is consistent with our hypothesized pathways.

Our paper builds on three important areas of research in development economics. First, a wide range of studies has explored how labor market participation, particularly among female household members, influences contraceptive use in developing countries. For example, in Togo, Gage (1995) found that women who work outside the home are significantly more likely to use modern methods of contraception. Anderson and Eswaran (2009), in Bangladesh, found that women working outside the home have greater bargaining power in household reproductive decisions. More recently, Van den Broeck (2020) found that employed Ugandan women are more likely to use contraceptive methods. Additional studies in developing countries have found that women's economic power leads to safer sexual relations with husbands and an increase in the intention to use family planning services (Gage 1995; Hogan, Berhanu, and Hailemariam 1999). Here, we build on this literature by exploring if jobs created as part of workfare program impact contraceptive use in similar ways.

Second, there is a broader development economics literature examining contraceptive use and family planning decisions in developing countries. This literature has revealed how family planning programs impact contraceptive use (Karra et al. 2022), birth rates (Joshi and Schultz 2013; McCarthy 2019), and other economic outcomes (Canning and Schultz 2012). For example, D'Exelle and Ringdal (2022) demonstrate that involvement in family planning meetings at a health center in rural Tanzania increases the uptake of contraceptives. Our study adds to this literature by providing evidence of public workfare programs and the use of contraceptives, which has ramifications for family planning and could also increase the labor force participation rate through increased use of contraceptives. This is particularly relevant in India, where policymakers are concerned about low female labor force participation.

Third, we contribute to a sizeable literature that studies the wide array of outcomes associated with public workfare/job guarantee programs. For example, existing literature has explored MGNREGA's impact on labor markets (Azam 2011; Imbert and Papp 2015; Zimmermann 2012; Muralidharan, Niehaus, and Sukhtankar 2017; Berg et al. 2018; Deininger and Minten 2002; Merfeld 2020), health (Chatterjee and Merfeld 2021; Chari et al. 2019; Dasgupta 2017), conflict (Fetzer 2020), agricultural productivity (Varshney, Goel, and Meenakshi 2018; Gazeaud and Stephane 2020), and human capital accumulation (Ajefu and Abiona 2019). For example, Ajefu and Abiona (2019) found that MGNREGA increased women's engagement in the labor market and reduced children's engagement in school in response to rainfall shocks. Chatterjee and Merfeld (2021) found that MGNREGA decreased sex-selection in children during lean agricultural seasons. Chari et al. (2019) found that MGNREGA increased neonatal mortality and Imbert and Papp (2015) and Zimmermann

(2012) reveal that MGNREGA raised private sector wages, especially for women.[3] In combination with the literature that has revealed the impact of labor market participation on family planning, the estimated impacts of MGNREGA reveal several pathways through which MGNREGA could affect contraceptive use across rural India.

By bridging the gap between workfare programs and contraceptive use, we highlight a previously unrecognized unintended consequence of workfare programs. By exploiting the rollout of labor market opportunities created by MGNREGA, we also provide insight into how labor market opportunities that include women's employment more generally can contribute to family planning in rural areas of developing countries. As developing economies diversify and women's participation in labor markets changes (Lahoti and Swaminathan 2016), this has potentially broad consequences for the future of rural economies across the globe.

The rest of this paper is organized as follows. In the next section, we provide relevant details on MGNREGA in India and how it may impact family planning and contraceptive choices. Then, we introduce the data and the empirical strategy followed by results. Finally, we discuss our results and provide conclusions.

2. Institutional background and impact pathways

In this section, we describe details of MGNREGA to further motivate how it could impact family planning and contraception decisions. We also describe the various impact pathways through which work programs can affect family planning.

2.1. National Rural Employment Guarantee Act

The National Rural Employment Guarantee Act, established in 2005, had the primary objective of enhancing livelihood security for households in rural areas of India by providing at least 100 days of guaranteed minimum wage employment in every fiscal year.[4] Common public work activities include water conservation and harvesting, drought-proofing for agricultural purposes, building irrigation canals, renovation of traditional water bodies, land development, flood control and protection, and rural transportation infrastructure improvements. The conditions of rural employment guaranteed by MGNREGA include that at least a third of the beneficiaries must be women with wages equal to those of men.[5] [6] The central government bears the major cost of the program, which includes the payment of wages and up to three-fourths of the material costs for public works. The state government is liable for unemployment allowances if a laborer is unable to find work within 15 days of looking for work, as well as the remaining material costs of the projects.

The scheme was rolled out in three phases across three years (2006, 2007 and 2008). In the first phase, 200 districts were included in the scheme, and 130 and 270 districts were included in the second and third phase respectively. The rollout was not random. The scheme targeted poor districts first. Critical to the empirical strategy of this article is the way MGNREGA was rolled out. We exploit this variation in implementation timing to estimate the impact of MGNREGA on the use of family planning methods among currently married women. Figure 1 shows a map of the three phases of the scheme roll out as well as how we group districts into treatment and control groups for our empirical analysis.

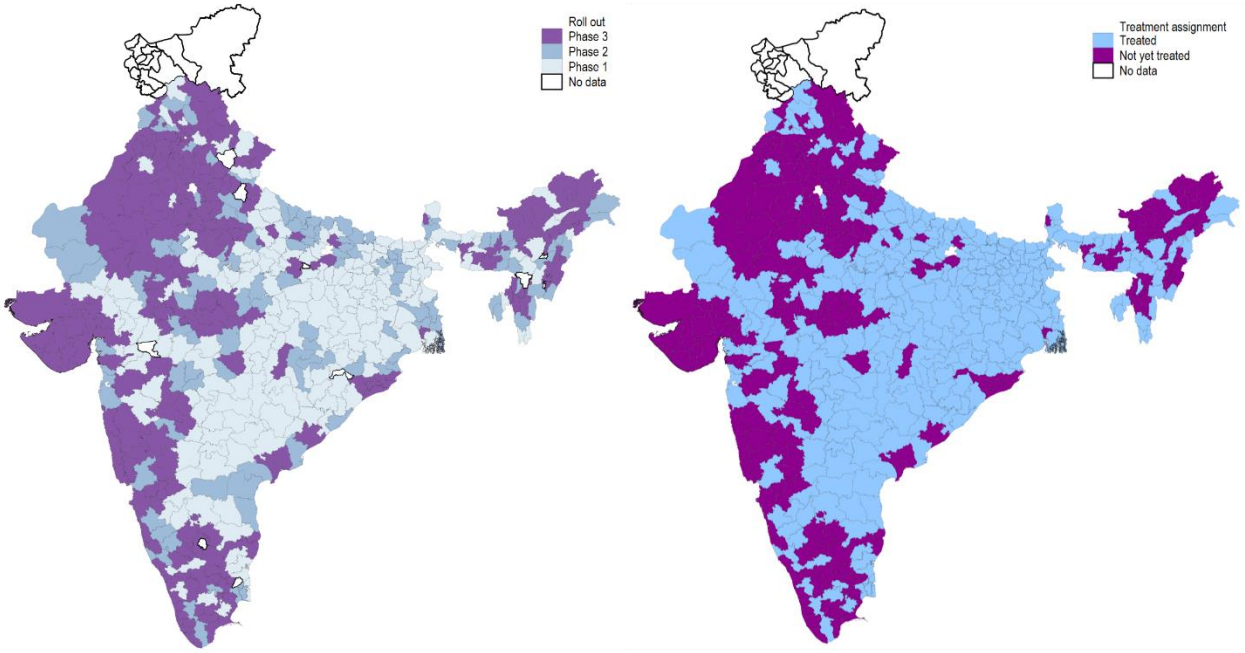

Figure 1a (left). The three phases of MGNREGA scheme roll out. Rural Indian districts color-coded to distinguish different phases. Source: Own calculation based on 2001 census boundaries. **Figure 1b (right).** Treatment assignment: Districts in Phases 1 and 2 are classified as treated, while districts in Phase 3 are classified as not yet treated (and serve as a control group in our analysis).

According to the Ministry of Rural Development in India, women constituted 54.5% of program participants in 2021-22, up from 40% in 2006-2007.[7] Existing evidence suggests that women's share of work under MGNREGA is greater than their share of work in the labor market across all states (Shah et al. 2015).[8] These facts suggest that MGNREGA had higher effects on employment for rural women than for rural men. Our goal is to examine if this led to changes in the use of contraceptives across rural India.

2.2. Impact pathways: jobs programs and contraceptive use

This subsection provides insight into the pathways through which MGNREGA may influence contraceptive use, and ultimately the number of children and the timing of births (see Figure 2). In Figure 2, the arrows indicate different impact pathways that connect MGNREGA to the

use of contraceptives. The boxes represent intermediate outcomes while the numbered arrows describe 5 different pathways that we hypothesize based on evidence in the existing literature. These pathways include 1) increased household income, 2) changes in female labor market participation, financial autonomy, and bargaining power, 3) changes in norms and attitudes towards contraception, and household income, 4) composition effects and selection, and 5) changes in the nature of work and demand for children. MGNREGA offers manual labor that can be a physically demanding task. In mechanism section, we empirically explore these pathways using our data.

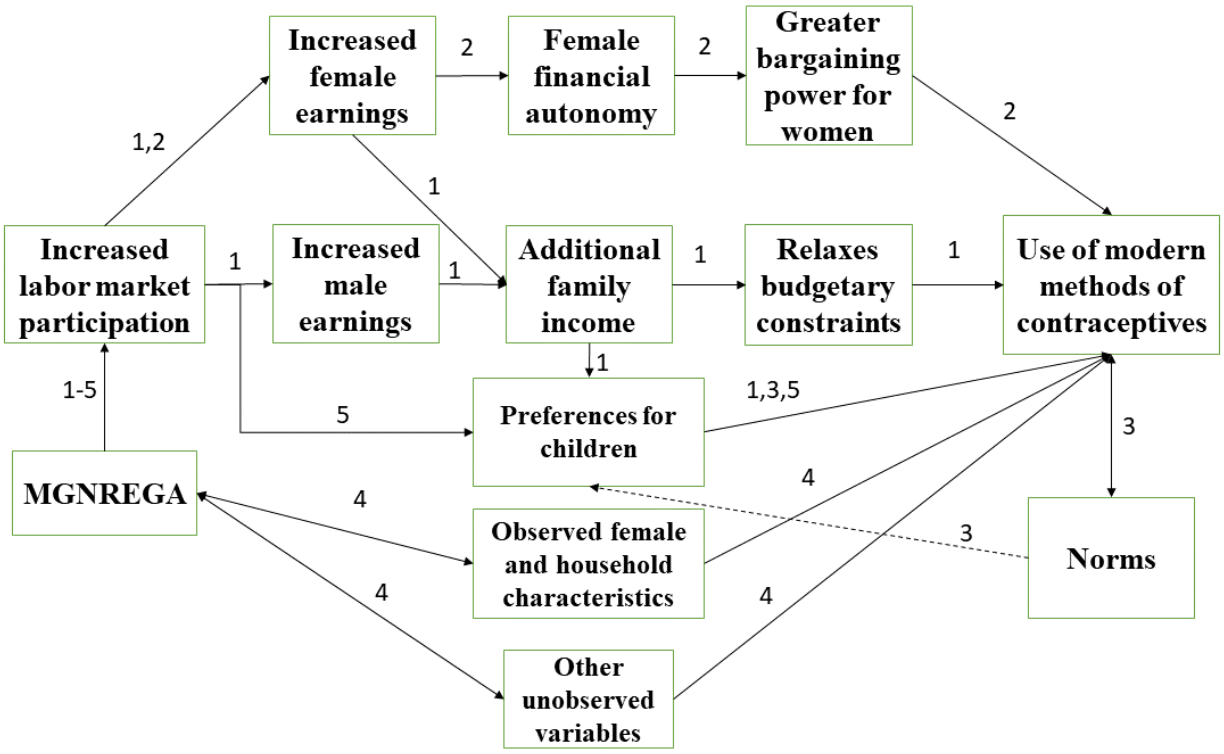

Figure 2. Mechanisms through which MGNREGA affects contraceptive use.

Note: Figure describes the pathways through which a job guarantee program can affect use of contraceptives. The boxes describe intermediate outcomes along each pathway while the numbers on the arrows label the 5 pathways: 1) increased household income, 2) changes in female labor market participation, financial autonomy, and bargaining power, 3) changes in

norms and attitudes towards contraception, and household income, 4) composition effects and selection, and 5) changes in the nature of work and demand for children.

3. Data and Descriptive Statistics

This section details the data used in our analysis. Our primary data source is the District Level Household and Facility Survey (DLHS), which provides data on women's reproductive health. We combine data from multiple sources to construct district-level variables used in the analysis (see Appendix Table A1 for a list of sources).

3.1. Data

We use the District Level Household and Facility Survey (DLHS) collected by the Indian Ministry of Health and Family Welfare to study reproductive choices, focusing on the use of family planning methods by married women. The DLHS is one of the largest demographic and health surveys carried out at regular intervals in India. The DLHS datasets are available from the International Institute for Population Sciences. In rural areas, DLHS employs a two-stage (many villages in a district) stratified sampling design.[9] Households are primary sampling units in the DLHS. We use rounds 2 and 3, collected in 2002-2004 (pre-treatment) and 2007-2008 (before which, Phases 1 and 2 had received the workfare program).[10][11] The surveys are repeated cross-sections of households which cover detailed questionnaires on topics of maternal and child health, family planning and other reproductive health services. DLHS datasets have outcome variables that include family planning methods, women's age at first birth, surviving number of children, and attitudes of husbands (and other family members) towards contraception.

3.1.1. MGNREGA districts: Treated versus not-yet-treated

As previously mentioned, MGNREGA was implemented in three phases. The first phase was rolled out in 2006, the second phase occurred in 2007, and the third phase was implemented in 2008. In order to combine DLHS data with MGNREGA treatment timing, we label districts in the first and second phases as treated (282 districts) and the districts in the third phase (198 districts) as not yet treated. Figure 1b shows a map of the treated and not yet treated districts. Poor districts were the focus of the first phase of rollout, resulting in non-random treatment assignments. The absence of a credible counterfactual may mean that the treatment and control groups do not have the same characteristics, and a simple difference in the outcome variable could lead to biased estimates. Following Gazeaud and Stephane (2020), we apply Inverse Probability of Treatment Weighting (IPTW) to match districts based on observable characteristics. We follow the literature (for example, (Merfeld 2020; Zimmermann 2012)) to include pre-program district-level characteristics such as total population, percent rural, district area, percent scheduled castes and tribes, percent literate, average monthly per capita consumption expenditure, average casual wage, female labor force participation rate, rainfall and growing degree days (the growing season is June through September, coinciding with the monsoon season in India).[12] Then we exploit the variation in timing of the treatment to employ a difference-in-differences (DiD) estimator. This DiD strategy compares the outcomes in households in districts included in the first and second phases (treated) to the households in districts included in the third phase (control).

3.1.2. Family Planning Methods

This section reviews the contraceptive methods available to women in the sample and their characteristics. The main dependent variable used in this analysis indicates if a married woman uses any family planning methods. This information was obtained from a question on

contraception and fertility preferences in the individual woman's questionnaire in the DLHS. Women were asked the question: Are you/your husband currently doing something or using any method to delay or avoid getting pregnant? If the woman reported that she was using any method, she was coded 1; if she reported she was not, she was coded 0.

To augment the analysis, we categorize the types of planning methods into modern and traditional family planning methods. Modern methods include permanent contraceptives, such as female and male sterilization; long-acting reversible contraceptives (LARCs), such as injectables and intrauterine devices: IUD/Copper-t/Loop; and oral pills, female condoms, and male condoms (*Nirodh*). Traditional methods include the use of rhythm, periodic abstinence, and withdrawal.

According to DLHS round 3 (2007-2008), about 72% of the users of modern contraceptive methods paid money to buy contraceptives such as intra-uterine devices, daily or weekly pills, female or male condoms, and injectables. Murro et al. (2021) shows that the annual cost of contraception varies between 11 and 397 Indian rupees (US $0.16 to $5.41) depending on the types of contraceptives used. In India, modern methods of contraceptives including oral pills, and female and male condoms do not require medical prescriptions and can be available over the counter but may require husband and or family members (especially the mother-in-law) approval, for example in the case of sterilization. Not all modern methods are easily accessible in rural areas depending on the socio-cultural norms and the community access to health care services. Therefore, there may be concern for supply constraints in rural areas of the country. For example, it is possible that birth control supplies changed at the same time as MGNREGA. However, according to the third round of the DLHS (2007-2008), less than 4% of contraceptive users in rural India ever faced difficulty in getting any methods

of family planning.[13] This provides suggestive evidence that supply is rarely the constraining factor in observed use of contraceptives. We also know of no national level program expanding contraceptives supplies that systematically correlated with the roll out of MGNREGA.

According to DLHS-3, in rural areas, about 41% of contraceptive users obtained contraception from private pharmacies/drugstores or private clinics/medical sector, followed by government medical facilities, including hospitals, dispensaries, mobile clinics, community workers (*anganwadi* and *asha* workers), and private shops (32% and 14%, respectively). The values are similar when disaggregated across treated and control districts. Private facilities accounted for 41% (43%) in treated districts, followed by 33% (30%) from government facilities and 13% (17%) from private shops. The values in parenthesis pertain to control districts. Among the members of rural Indian households that have ever used contraceptives, a little less than three-fourths paid money in 2007-2008 for pills, female or male condoms, or injectables.

3.2. Descriptive Statistics

In the second round of the DLHS (2002-2004), data were collected on 507,622 women aged 15 to 44 who are currently married. In the third round (2007-2008), data were collected on 643,944 ever-married women aged 15 to 49 and 166,620 unmarried women aged 15 to 24. From these data, we focus on the sample of currently married women aged 15 to 44 who are not currently pregnant. Under the MGNREGA Act of 2005, individuals 18 years of age or older are eligible to work under the program. Therefore, we restricted the sample to women 18 years of age and older. The resulting sample includes 292,810 women in 2002-2004, and 350,210 women in 2007-2008.

Table 1. Individual Summary Statistics

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (p-val.)
Outcomes (including all women in the sample)			
Any family planning methods	0.551	0.517	0.282
	(0.497)	(0.499)	
Any modern methods	0.478	0.438	0.179
	(0.500)	(0.496)	
Any traditional methods	0.074	0.079	0.638
	(0.261)	(0.269)	
Among women who are currently taking contraceptives			
Female sterilization	0.663	0.630	0.260
	(0.473)	(0.483)	
Male sterilization	0.022	0.018	0.365
	(0.147)	(0.133)	
Intrauterine Devices (IUDs)	0.033	0.044	0.128
	(0.180)	(0.204)	
Oral pills	0.071	0.081	0.446
	(0.256)	(0.273)	
Condom	0.072	0.073	0.928
	(0.258)	(0.260)	
Rhythm/Periodic abstinence/Withdrawal	0.122	0.144	0.234
	(0.327)	(0.351)	
Individual-level characteristics			
Women age in years	30.466	30.701	0.097
	(7.262)	(7.230)	
Women can read or write	0.466	0.449	0.524
	(0.499)	(0.497)	
Spouse can read or write	0.713	0.698	0.407
	(0.452)	(0.459)	
Number of children	2.671	2.762	0.275
	(1.664)	(1.755)	
Household-level characteristics			
Religion: Hindu	0.800	0.710	0.085
	(0.399)	(0.456)	
Scheduled Castes/Tribes	0.351	0.393	0.347
	(0.477)	(0.489)	

Note: The IP-weighted mean is reported. Standard deviations are in parentheses. Sample is restricted to common support region. Treated includes phase one and two districts, and control includes phase three districts. The third column, difference, is calculated with WLS regressions (using IP-weights) and clustered standard errors at the district level. Source: DLHS round 2 (2002-2004).

Table 1 presents the individual summary statistics, IP-weighted, by treatment groups. More than half of currently married women in treatment and untreated districts used family planning methods. About 48% used modern contraception in treated districts and about 44% in untreated districts. Fewer than 10% of currently married women used traditional contraceptive methods in both treated and untreated districts. In our sample, women's sterilization is the most common modern method and men's sterilization is the least common method of contraception. Oral pills, and male and female condoms remain very low, with less than 8% of rural married women currently taking contraceptives using these methods. Intrauterine devices (IUDs) are used by less than 5% of rural married women currently taking contraceptives in both treated and untreated districts. Traditional methods were used by approximately 12% of rural married women who are currently using contraceptives in treatment districts and 14% in untreated districts. Appendix Table A2 presents individual summary statistics before the match.

In our analysis, we control for women's age, the reading or writing abilities of women and their husbands, the number of surviving children, membership in social groups (an indicator equal to one if a household belongs to scheduled castes/tribes), and religious affiliation (an indicator of whether a household is Hindu). On average, the age of women is about 30 years old and less than half can read or write. Slightly less than three-fourths of husbands in the sample can read or write. 35% of households in treated districts belong to scheduled castes while 39% do in untreated districts.[14] Married women in rural areas bore just under 3 children, on average, in both treated and untreated districts. The usage of modern methods of contraceptives varies by women's age: 42% (39%) of married women under 35

years old used modern methods of contraception, while 62% (55%) of married women aged 35 years and older used modern methods of contraception in treated (untreated) districts.

Table 2. District Summary Statistics

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (p-val.)
Propensity score	0.540	0.580	0.412
	(0.309)	(0.264)	
Total Population (in thousands)	1685.455	1423.395	0.125
	(1374.647)	(1140.525)	
Percent rural	0.791	0.799	0.674
	(0.145)	(0.114)	
Area (in square km)	116.355	109.100	0.650
	(143.130)	(135.001)	
Percent Scheduled Castes	0.157	0.141	0.282
	(0.088)	(0.094)	
Percent Scheduled Tribes	0.143	0.218	0.209
	(0.223)	(0.344)	
Percent Literate	0.547	0.535	0.457
	(0.118)	(0.100)	
Average MPCE	3524.572	3466.498	0.704
	(1057.067)	(1076.334)	
Average casual wage	329.410	334.066	0.671
	(134.240)	(133.176)	
Labor force participation rate	0.657	0.669	0.493
	(0.089)	(0.105)	
Female labor force participation rate	0.201	0.220	0.225
	(0.095)	(0.106)	
Rainfall (mm)	1217.950	1404.769	0.268
	(712.139)	(1113.264)	
Growing degree days	2366.131	2251.824	0.207
	(462.101)	(603.619)	
Number of observations	152,370	104,455	571,080
Number of districts	282	198	480

Note: Standard deviations are in parentheses. Sample restricted to common support region. Treated includes phase one and two districts, and control includes phase three districts. The third column, difference, is calculated with WLS regressions and clustered standard errors at the district level. MPCE refers to the monthly per capita consumption expenditure. Average MPCE and casual wage are in 2004-2005 prices.

Table 2 presents district-level summary statistics. There are 282 districts in the treated group and 198 districts in the control group. Examining point estimates, treatment districts tend to be slightly larger and more populated on average. Compared to control districts, treated districts have a slightly greater percentage of scheduled castes, but a lesser percentage of scheduled tribes. Both groups have similar literacy rates. Additionally, households in both groups have similar average monthly per capita consumption expenditures (MPCE) of around 3,500 Indian rupees. The labor force participation rate is about two thirds in both groups. Control districts have more rainfall than treated districts on average. The p-value in column 3 of Table 2 indicates that district-level variables do not statistically differ across (matched) treated and untreated districts.

4. Econometric Specification and Identification

We estimate the impact of MGNREGA on family planning decisions by exploiting the rollout of MGNREGA at the district level. As mentioned before, districts in Phases 1 and 2 are in the treated group, while districts in Phase 3 are in the control group. We explore outcomes that result from MGNREGA, such as the use of contraception, the age of women at first birth, the number of children born, and attitudes of husbands (and other family members) towards contraception.[15] Our main estimating equation is given by

$$y_{ihdt} = \beta_0 + \beta_1 MGNREGA_d * Post_t + \xi X_{ihdt} + \alpha_d + \phi_{st} + \lambda_{mt} + \varepsilon_{ihdt} \qquad (1)$$

where y_{ihdt} is the use of family planning methods for (female) individual i in household h in district d at time t; $MGNREGA_d$ is a dummy variable, equal to 1 if the public workfare program is available in district d in (or prior to) 2006-2007 (it represents our treatment designation); $Post_t$ is a dummy variable equal to one for DLHS round 3 (2007-2008) when MGNREGA had been implemented in treated districts ; X_{ihdt} includes a set of individual and

household-level controls. Individual characteristics include age, an indicator of whether a woman can read or write, an indicator of whether her husband can read or write, and the number of children she has given birth to that survived. Household characteristics include religious and social groups. α_d are district fixed effects, which control for time-invariant characteristics of each district that could impact the use of contraceptives ($MGNREGA_d$ is absorbed by this fixed effect); ϕ_{st} are state-year fixed effects which control for common time-varying shocks at the state level (this includes $Post_t$). For example, because healthcare is a state-level service in India, different states have different health-related policies, infrastructure, and services that change over time. λ_{mt} is a fixed effect for the month and year that survey data were collected; and ε_{ihdt} is the error term. We cluster the standard errors at the level of treatment (district).

The coefficient of interest is β_1, which measures the average effect of MGNREGA on the outcome of interest and is interpreted as the intention to treat (ITT) because in the DLHS dataset, we do not directly observe who participated in MGNREGA. Our identification strategy compares treated districts that received MGNREGA in 2007-2008 to those that had not yet received it in 2007-2008. Our data include observations from 2002-2004 (DLHS-2, when no districts have been treated) and 2007-2008 (DLHS-3, Phase 1 and 2 districts have been treated, but Phase 3 districts have not yet been treated).

4.1. Identification strategy

The major threat to identification is that confounding variables that determine treatment may also affect the outcome variable. By including additional observable controls in our main estimating equation (1), we take into account the observable confounding variables but there may still exist unobserved confounding variables that could bias coefficient estimates.

As MGNREGA was targeted toward poor districts rather than randomly allocated, constructing a credible counterfactual is important. The first threat to identification arises from non-random assignment of treatment districts. In the absence of a credible counterfactual, the treatment and control groups may not be equivalent in their characteristics and, therefore, a simple difference in the outcome variable may bias the estimates. In the literature (e.g., Merfeld (2020)), the above concern has been addressed by including the variables used to rank districts to determine program eligibility- the proportion of scheduled castes/tribes, the agricultural productivity, and the agricultural wages - on the right hand side of the econometric equation. To control for these, we use IP-weighted matching methods to match district characteristics in the main econometric specification. The IP-weighted technique is a propensity score-based method which aims to achieve a balanced distribution of confounding factors across treatment groups. The result is more robust and produces less biased estimates of the impact of treatment (Allan et al. 2020). Although, the IPTW helps to create a balanced treatment and control group, conditional on observables. Unobservable confounding variables could still result in bias.

We estimate this specification using weighted-least-squares, where the weights are determined by the inverse probability of treatment weighting techniques. The Weighted Least Square (WLS) estimator is used for all regressions.[16] In the following sub-section, we explain how we implement this estimator.

4.1.1. Inverse probability of treatment weighting

Following Gazeaud and Stephane (2020), we use the logit estimator to compute the inverse probability of treatment weight:

$$Treated_d = f(\beta_0 + X_d'\beta) \quad (2)$$

where X_d is a vector of district-level variables that influence the probability of belonging to the treated group. f is the logistic function. As mentioned earlier, rollout was targeted at poor districts which were defined on the basis of variables at the district level. Following Zimmermann (2012) and Merfeld (2020), we include total population from the 2001 Census, as well as the percent rural, area (in square km), percent scheduled castes, percent scheduled tribes, percent literate, average monthly per capita consumption expenditure (2004-2005 prices), average casual wage (2004-2005 prices), labor force participation rate, female labor force participation rate, rainfall, and growing degree days for 2004. We use the logistic regression prediction to calculate propensity scores and then derive the inverse probability (IP) of treatment weight as one over the predicted probability.[17] In order to balance the treated and control groups conditional on observed baseline covariates, the weights are assigned to observations based on the inverse of their probability of receiving treatment, as estimated by the propensity score. For example, if a district receives treatment with a high probability, it is given less weight than a district with a low probability. Appendix Table A3 shows the logistic regression predicting treatment.

Figure 3 shows the distribution of propensity score by treatment groups. The area within the dashed line represents the common support. The highest propensity score for untreated is 0.96 and the lowest propensity score for treated is 0.04. The presence of high propensity scores for treated groups and low propensity scores for untreated groups may cause concern. We address this issue by restricting our sample size to the common support region, which eliminates very high and low propensity scores from the sample.[18]

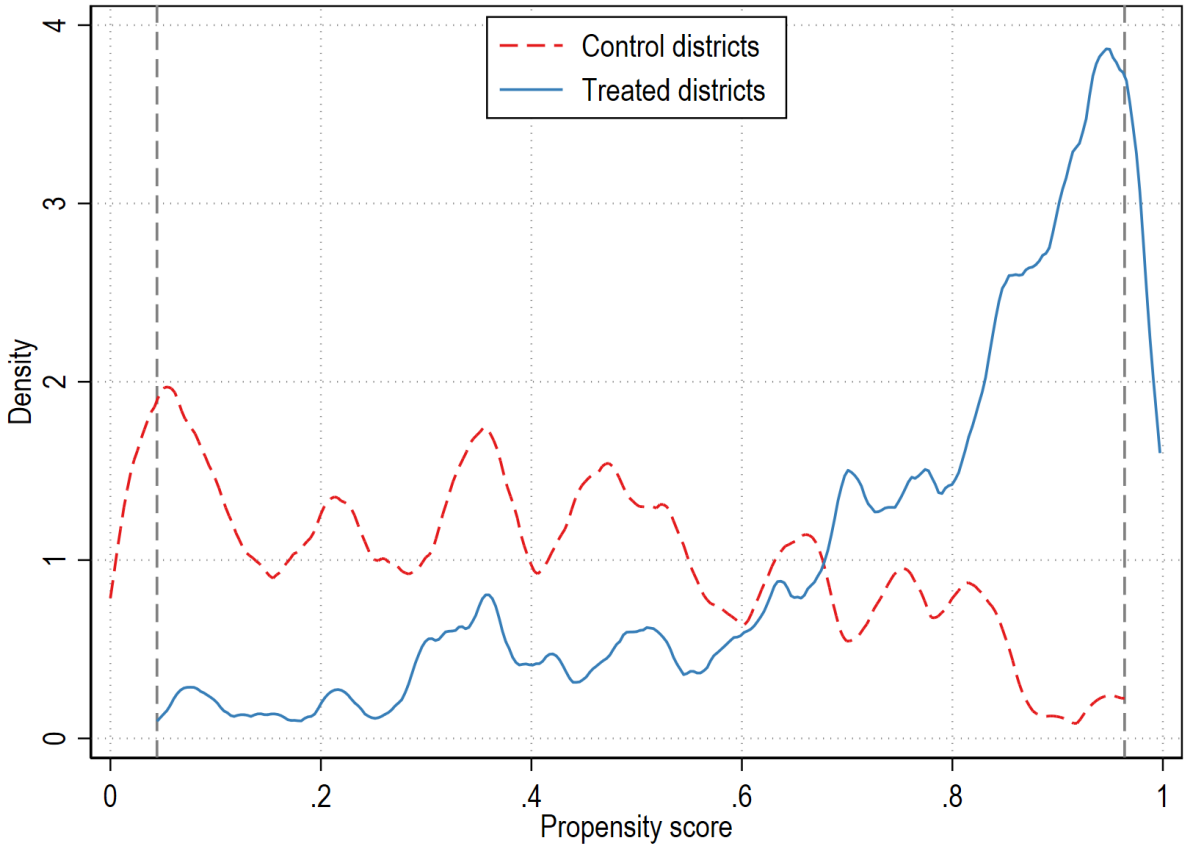

Figure 3. Propensity score distribution by treatment groups.

Note: The area within the dashed lines represents the common support. The highest propensity score for untreated is 0.964 and the lowest propensity score for treated is 0.044. Source: Own calculation.

4.1.2. Alternative specification: continuous treatment variable

We also estimate a model that considers the number of years the workfare program has been in place in a given district. The estimating equation is

$$y_{ihdt} = \gamma_0 + \gamma_1 Exposure_{dt} + \xi X_{ihdt} + \alpha_d + \phi_{st} + \lambda_{mt} + \varepsilon_{ihdt} \qquad (3)$$

where $Exposure_{dt}$ is a non-negative integer counting how many months MGNREGA has been present in district *d* at time *t*. The remaining terms are the same as in Eq. (1). We exploit

the interview months to vary the duration of exposure. We use three phases of the program rollout to construct exposure variables over months:

- We assign 12 months plus interview months to households in phase 1 of the third round of DLHS interviews in 2007, and 24 months plus interview months to households in phase 1 of the interview in 2008.
- We assign interview months to households in phase 2 of the third round of DLHS interviews in 2007, and 12 months plus interview months to households in phase 2 of the interview in 2008.
- We assign zero months to phase 3 districts in third round of DLHS.

For example, household A in the treatment district of phase 1 interviewed in July 2008 would receive an exposure value of 31 (2*12 + 7 = 31); and household B in the same district interviewed in August 2008 would receive a value of 32 (2*12 + 8 = 32). Appendix Figure A1 shows substantial variations in the exposure variable.

4.1.3. Pre-Program Trends and Event study specification

The identification strategy requires that the trend in outcomes of the treatment group moves in parallel with the comparison group. We leverage Demographic and Health Survey (DHS) data from 1992/93 and 1998/99 to create longer pre-trends. Appendix Figure A2 displays the pre-program trends for our outcome variables: any family planning methods, woman's age at first birth, family size, and husband's (and other family members) opposition to female contraception. There is evidence to support a parallel trend in outcome of interest.

To investigate pre- and post-program differences, we include DHS rounds (1992/93 and 1998/99) and DLHS rounds (2002/04 and 2007/08) in a single specification and performing

an event-study in addition to the traditional DiD. DHS rounds (1992/93 and 1998/99) and DLHS-2 (2002/04) are pre-program surveys. The specification for an event-study regression is given by

$$y_{ihdt} = \sum_{j=-2, j\neq -1}^{1} \beta_j int_{ihdt}^{j} + \alpha_d + \phi_{st} + \lambda_{mt} + \varepsilon_{ihdt} \quad (4)$$

where j denotes leads and lags of the event of interest. int_{it}^{j} represents an interaction term between DHS and DLHS rounds and treatment status, that is, MGNREGA x Post x DHS and DLHS round. The fixed effects are defined as in Equation (1). The event-study regression omits the category from the DLHS-2 (2002/04).

5. Econometric Results

In this section, we present our empirical results, including our main results describing the total impact of MGNREGA on contraceptive use in rural India. We also explore the impacts on the age of first birth for mothers, the number of surviving children in our study region, and family attitudes towards contraception. We provide further evidence of program impacts by presenting results that examine how impacts change with the length of time the program has been in an area. We then provide a range of robustness checks, including an event study specification, changing controls, and using different weights and matching methods. In Appendix Table A4, we show the results of a placebo test in which we use round 1 of DLHS (1998/99) as the pre-program period and round 2 of DLHS (2002/04) as the post-program period. To do this, we re-estimate the main specification (without controls because, as mentioned in the footnote of the data section, we are unable to identify the individual- and household-level controls for DLHS round 1). This placebo regression provides suggestive

evidence in support of the parallel trends assumption in our context, as indicated by the insignificant treatment effect.

5.1.Main results

Our main results consist of the impacts of MGNREGA on the use of contraceptives, family outcomes including the age of mothers at first birth and the number of children per household, and family members' attitudes towards contraception.

5.1.1. Use of contraceptives

Table 3 presents the main results from Equation (1) using IP-weights and restricted to the common support region. The results suggest an increase of 1.8 percentage points (a 3.2% increase over the sample mean) in the use of family planning methods in treated districts. The use of modern methods shows an increase of 1.4 percentage points (approximately 3% increase over the sample mean). The estimate for any traditional methods of family planning is positive, but statistically insignificant at conventional level of significance. The covariates indicate that as a woman's age increases by one year there is a 1.4 percentage point increase in contraception use. Moreover, women and their spouses who can read or write have a positive association with using contraception. Importantly, the coefficients are statistically significant and have a magnitude that is larger than the workfare program, at 5.7 percentage points. Contraceptive use is positively associated with the number of children and households belonging to Hinduism, while households belonging to scheduled caste/tribes have lower use rates.

5.1.2. Women's age at first birth and family size

Next, we show how MGNREGA's availability is associated with the timing of a woman's first child and the number of children born. Column 4 of Table 3 reports the impact of MGNREGA on women's age at first birth.[19] The results suggest an increase in women's age at first birth in treated districts by 0.11 years or 1.32 months.[20] Although, this number appears to be small, it may potentially indicate that MGNREGA allows some women to work longer before having their first child. To our knowledge, this is a novel result in the literature and future work should explore if women choose their age at first birth in response to economic conditions. Women's (and their husbands') ability to read or write has a positive and significant effect on their age at first birth. Unsurprisingly, the number of children women have is negatively associated with their first birth age, which suggests that women start childbirth early. Hindu households and households belonging to scheduled castes/tribes have a negative association with women's age at first birth. Next, the treatment effect on the number of children born is not different from zero (column 5 of Table 3).

5.1.3 Impact on attitudes towards contraception

Recent studies in developing countries (see e.g., the systematic review of Maxwell et al. (2015)) have shown that various forms of intimate partner violence, including reproductive coercion, are associated with lower use of contraceptives. Indian women in rural areas exposed to domestic violence have a lower level of autonomy and, as a result, may be less able to negotiate around fertility and contraceptive use (Stephenson, Jadhav, and Hindin 2013). We do not observe direct spousal violence in the DLHS dataset, but we do observe opposition to women's contraception from the husband and other family members. According to the DLHS round 3, 11% of women who did not use contraception said their husband opposed it and 0.5% said other family members opposed it.[21]

To explore if family attitudes towards birth control change after MGNREGA, we construct a dummy variable equal to 1 if husband and other family members' opposition was a reason not to use contraceptives and 0 otherwise. Column 6 of Table 3 reports the results from the full sample (women who are currently using contraceptives and who are not using). The negative sign of the average treatment effect coefficient suggests that the introduction of MGNREGA reduced opposition from the husband and other family members as a reason not to use contraceptives in treated districts. The estimated coefficient in column (6) of Table 3 has a very small magnitude and is significant only at the 10 percent significance level. Notably, having an educated husband has larger effect on attitudes towards female contraception. Women's age and the number of children born to them are negatively associated with family members' opposition to contraception.

In Column (7), Table 3, the results are reported after restricting the sample to women who are not currently using any family planning methods. In this model, the estimated coefficient effect suggests a negative association between workfare programs and opposition to contraceptive use from husbands and other family members, although it is statistically insignificant. These results suggest possible changes in attitudes with the introduction of a workfare program.

Table 3. Impacts of MGNREGA on Family Planning, Birth Outcomes, and Family Attitudes

	Contraceptive use			Birth outcomes		Family member opposition to contraception	
	Any methods	Any modern methods	Any traditional methods	Woman's age at first birth	Number of children born	Full sample	Restricted sample
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
MGNREGA x Post	0.018**	0.014**	0.004	0.119***	0.013	-0.005*	-0.010
	(0.008)	(0.006)	(0.005)	(0.046)	(0.020)	(0.003)	(0.013)

Individual- and household- level controls

Women's age in years	0.014***	0.014***	-0.0002*	0.168***	0.132***	-0.001***	-0.003***
	(0.0004)	(0.0004)	(0.0001)	(0.005)	(0.003)	(0.000)	(0.000)
Women can read or write	0.057***	0.043***	0.014***	0.670***	-0.411***	-0.001	-0.001
	(0.005)	(0.004)	(0.001)	(0.023)	(0.017)	(0.001)	(0.004)
Spouse can read or write	0.056***	0.048***	0.008***	0.088***	-0.195***	-0.001*	0.001
	(0.003)	(0.003)	(0.001)	(0.019)	(0.016)	(0.001)	(0.004)
Number of children	0.043***	0.038***	0.005***	-0.735***	n.a.	0.002***	-0.001
	(0.003)	(0.003)	(0.001)	(0.018)		(0.000)	(0.001)
Religion: Hindu	0.094***	0.090***	0.004	-0.124*	-0.336***	0.0001	0.014***
	(0.012)	(0.012)	(0.003)	(0.069)	(0.052)	(0.001)	(0.005)
Scheduled castes/tribes	-0.042***	-0.039***	-0.003**	-0.092***	0.215***	-0.0001	-0.005
	(0.005)	(0.006)	(0.001)	(0.023)	(0.020)	(0.002)	(0.003)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	0.558	0.486	0.072	19.36	3.071	0.018	0.114
Observations	570,193	570,193	570,193	525,175	570,193	570,193	90,169
Number of districts	480	480	480	480	480	480	480
R-square	0.220	0.227	0.091	0.275	0.393	0.047	0.090

Notes:
[1] The binary dependent variables indicate whether a married woman uses any family planning methods in column (1), any modern methods in column (2), and any traditional methods in column (3).
[2] The term 'any methods' refers to individuals currently using family planning methods. Modern methods include sterilization of women and men, using IUDs/copper-t/loop, oral pills, male and female condoms, and other modern methods. Traditional methods include using rhythm, periodically abstaining, withdrawing, and other methods.
[3] MGNREGA is a dummy variable, 1 for district that has implemented the workfare program. Post is a dummy variable that indicates that the observation is from the 2007/08 round of DLHS.
[4] The dependent variable in column (6)-(7) is binary, 1 for opposition from husband and family members as reason for not using contraceptives and 0 otherwise. Column (6) contains a full sample of women who are currently using all forms of contraceptives and women who are not currently using them. Column (7) restricts the sample of women who are not currently using any methods of contraceptives.
[5] The sample is limited to common support and excludes pregnant women.
[6] WLS estimator is used for all regressions using IP-weights. Robust standard errors in parentheses are clustered at the level of treatment (district).
[7] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

5.2. Impact of time exposed to MGNREGA

Table 4 presents the results from models that use the number of months the workfare program has been in place as the treatment variable. The number of months MGNREGA has been present in a district is labeled "exposure". Table 4 shows the impact of time exposed to MGNREGA on family planning methods, woman's age at first birth, and husband (and family members) opposition to female contraception. On average, one month of increased

exposure to the workfare program increases family planning methods by 0.1 percentage point and decreases the age of first birth for women by 1 percentage points. This translates into an increase of 2.1 percentage points in contraceptive use, and a delay of 6 months for the first birth over the sample mean, with an increase of one year increase in the program.[22] We find a negative association between time exposed to MGNREGA and opposition to female contraception from the husband (and family members), although statistically insignificant.

Table 4. Impact of time exposed to MGNREGA on family planning methods, woman's age at first birth, and husband (and family members') opposition to female contraception.

	Any methods	Woman's age at first birth	Husband and family members opposition to female contraception
	[1]	[2]	[3]
Exposure	0.001***	0.010***	-0.0001
	(0.0003)	(0.002)	(0.001)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.558	19.364	0.114
Observations	570,193	525,175	90,169
Number of districts	480	480	480
R-square	0.220	0.275	0.101

Notes:
[1] Exposure is a measure of how many months MGNREGA has been present.
[2] Individual controls include woman's age, an indicator of whether a woman can read or write, an indicator of whether her husband can read or write, and the number of children she has given birth to that survived. Household controls include an indicator of whether a household is Hindu and whether a household belongs to scheduled castes/tribes. We also include district, state-by-year, and interview month-year fixed effects.
[3] All regressions are limited to common support and exclude current pregnant women. In addition, the sample in column (3) is limited to women who are not currently using any family planning methods.
[4] Robust standard errors in parentheses are clustered at the level of treatment (district).
[5] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

5.3.Event Study

Figure 4 shows event-study coefficients and 95% confidence intervals for our outcome variables: any family planning methods (upper left), woman's age at birth (upper right), family size (bottom left), and husband's opposition to female contraception (bottom right). The omitted category is DLHS-2 (Event Time = -1). Event-study regression results show that for all the outcomes except for woman's age at first birth, the pre-treatment period (in figure 4, the event time is -3, -2), the coefficient of interest is statistically insignificant. This shows that for each period before the treatment, the treated and control groups are statistically the same. The estimated coefficients for any family method and family size in the post-treatment period (in figure 4, the event time is 1) are 0.028 and 0.063, and both are statistically significant. This evidence further supports that the control and treated groups had parallel trends, strengthening the DiD framework. In treated districts, the age of a woman at first birth was positive and statistically significant prior to the program, suggesting that the parallel trend assumption may not hold for that variable. Finally, the opposition to female contraception from husbands (and other family members) before and after the program is negative and statistically insignificant.

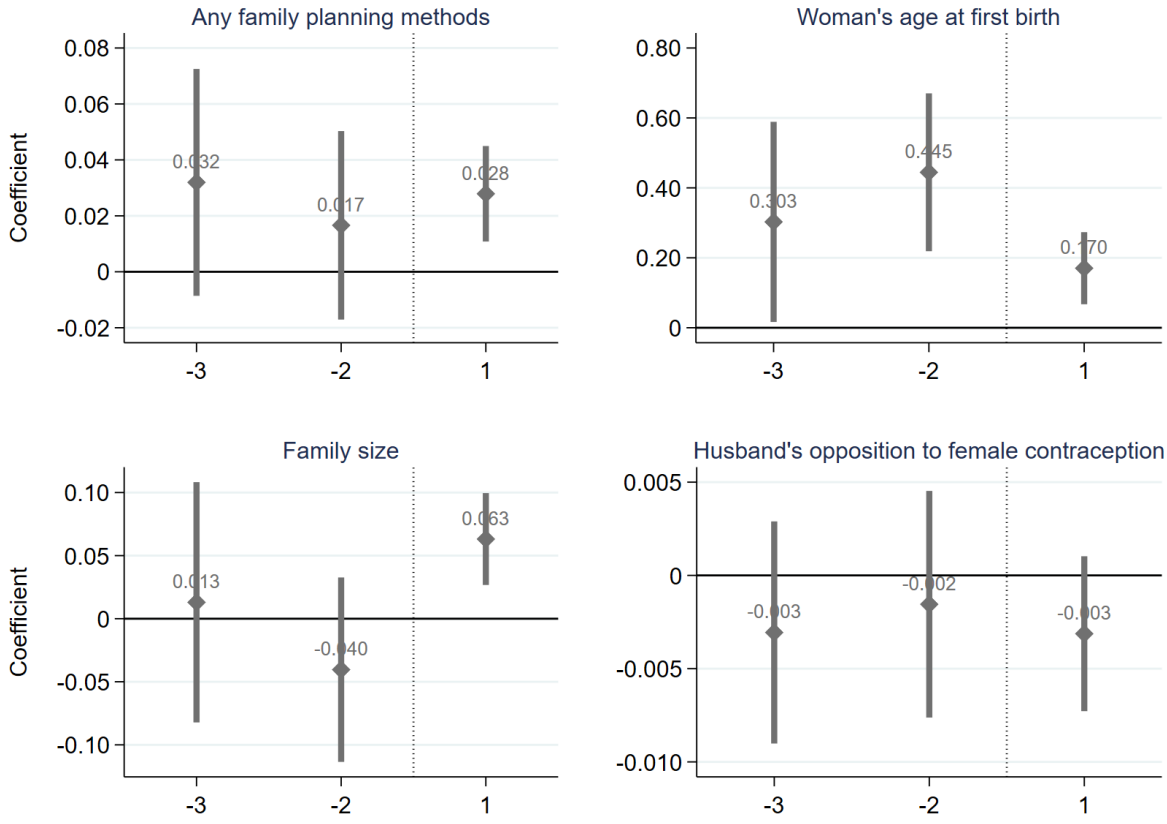

Figure 4. Event-study regression.

Note: The omitted category is DLHS-2 (Event Time = -1). The pre program data comes from the DHS rounds (1992/93 and 1998/99) and DLHS-2 (2002/04), and the post program data comes from DLHS-2 (2007/08).

5.4. Robustness checks

Our main results are robust to a number of robustness checks. First, matching reduces selection bias but does not remove it entirely because we are limited to matching on observable variables. Therefore, changes in other confounding factors that could produce a deviation from parallel trends could remain. Coefficient stability with and without controls provides suggestive evidence that omitted factors are not driving results. For example, if coefficient estimates do not vary with and without controls, then the omitted variables would have to correlate with the arrival of MGNREGA and not the included controls (Schlenker,

Hanemann, and Fisher 2007). Therefore, we estimate our main specification with and without including controls. Column (1) of Table 5 reports results without any controls. Second, DLHS provides survey sample weights. We re-estimate our main specification using the DLHS survey weights and the results are unchanged (column (2) of Table 5). Third, we include the estimated propensity score of being in the treated district on the right-hand side of the main regression Equation (1) as an additional variable. Fourth, we perform a matched DID with coarsened exact matching algorithm. We employ the coarsened exact matching method, an alternative to IPTW, in matching to reduce the imbalance in covariates between treated and control groups (Iacus, King, and Porro 2012).[23] Fifth, as the dependent variables are binary, we use the probit specification to estimate the impact of MGNREGA on the use of family planning methods. Column (5) of Table 5 reports the probit regression coefficient. Sixth, as previously discussed, the distribution of propensity scores for treated and untreated districts are skewed. This may arise from the presence of very high propensity scores for treated and very small propensity scores for untreated and may influence the estimates. The trimming process addresses the above concern by removing very high and low propensity scores from the sample. We calculate the 5^{th} centile of the propensity score in the treated and 95^{th} centile in the untreated and remove all observations that are not within these limits. In column (7), the regression results for a subset of star states are displayed. The stars represent seven states that have implemented the program with relative success compared to others (Imbert and Papp 2015).[24] The statistical significance of estimated coefficients fades away. It is important to note that the average contraception use in the star states is higher than the mean dependent variable from the full sample (0.60 and 0.56. respectively). We report these

regression results in Table 5. Overall, the findings are qualitatively the same as those in column 1 of Table 3 regarding contraceptive use.

Table 5. Robustness Checks

	Without controls	DLHS survey weights	Propensity score	Coarsened Exact Matching	Probit	Trimming	Star States
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Panel A: Any family planning methods							
MGNREGA	0.019**	0.022***	0.025***	0.017***	0.058**	0.020*	0.012
x Post	(0.008)	(0.007)	(0.008)	(0.008)	(0.024)	(0.011)	(0.013)
Number of districts	480	536	536	536	480	252	152
Observations	571,076	630,173	630,173	450,443	570,183	297,492	174,686
Panel B: Woman's age at first birth							
MGNREGA	0.096*	0.198***	0.195***	0.136***	n.a.	0.095	0.075
x Post	(0.053)	(0.049)	(0.043)	(0.042)		(0.058)	(0.059)
Number of districts	480	536	536	536	n.a.	252	152
Observations	525,921	580,610	580,610	415,896	n.a.	274,039	159,973
Panel C: Husband and family members opposition to female contraception							
MGNREGA	-0.010	-0.008	-0.003	-0.007	-0.028	-0.017	-0.019
x Post	(0.013)	(0.011)	(0.012)	(0.0124)	(0.084)	(0.020)	(0.035)
Number of districts	480	536	536	536	473	252	152
Observations	90,233	100,015	100,015	67,993	89,570	45,341	19,449

Notes:

[1] Individual controls include woman's age, an indicator of whether a woman can read or write, an indicator of whether her husband can read or write, and the number of children she has given birth to that survived. Household controls include an indicator of whether a household is Hindu and whether a household belongs to scheduled castes/tribes. We also include district, state-by-year, and interview month-year fixed effects.

[2] Column (2) reports results using DLHS survey reports in the main econometric specification.

[3] Column (3) reports results after including the propensity score as an additional regressor in the primary equation (1).

[4] Column (4) reports results using coarsened exact matching algorithm, alternative to IP-weights. The coarse variables used in the algorithm are woman's age, an indicator of whether a woman can read or write, an indicator of whether her husband can read or write, the number of children she has given birth to that survived, an indicator of whether a household is Hindu and whether a household belongs to scheduled castes/tribes, and household wealth index. The match summary consists of 225,420 matched on 242,257 observations for control and 225,420 matched on 388,895 for treatment.

[5] Column (5) reports coefficient estimates from the probit regression. In addition, IP-weights are applied, and the sample size is limited to common support.

[6] The column (6) shows the sub-sample results when trimming at the fifth centile using IP-weighted estimation. The sample is constructed by using the 5th centile of the propensity score in the treated and 95th centile in the control and removing any observations that are outside these limits.

[7] Column (7) shows the sub-sample results when sample size is restricted to seven star states, which account for the majority of employment generated by the program, using IP-weighted estimation.

[8] Robust standard errors in parentheses are clustered at the level of treatment (district).

[9] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

6. Pathways: An empirical exploration of mechanisms

In this section, we provide evidence for five pathways through which MGNREGA may affect the family planning methods used in rural India. To empirically examine these pathways, we combine DLHS datasets with the National Sample Survey for Employment and Unemployment Situations (NSSEUS) in India.

6.1. Changing labor market participation

In our conceptual framework, we noted that the direct way in which MGNREGA affects outcomes in the economy is through changes in labor market participation in a district. All pathways flow from this direct impact. Therefore, we present evidence that MGNREGA affects labor market participation. In Table 6, we summarize the effect of MGNREGA on women's labor market outcomes. We find that female labor force participation increased in treated districts compared to control districts. Furthermore, married women's daily wages in treated districts increased by 6.5 percentage points when compared to control districts. Our empirical results support the existing evidence in the literature (Imbert and Papp 2015; Zimmermann 2012; Berg et al. 2018; Deininger and Minten 2002; Merfeld 2020) that shows that MGNREGA did in fact alter labor market participation in rural India. We now examine how this direct impact affected contraceptive use through the 5 pathways hypothesized in our conceptual framework.

6.2. Household income

We first explore the extent to which MGNREGA increased household incomes, potentially relaxing budget constraints and allowing households to buy costly modern contraceptive methods. A study by (Gehrke 2019) shows that farmers have generated higher returns by

producing high-value crops. MGNREGA has enabled farmers to switch to high-value (but riskier) crops and, as a result, to higher profits. Although this study is based on only one state in India: Andhra Pradesh.

We do not observe household income in our dataset. While we observe the monthly consumption expenditure of households per capita (MPCE) and use it as a measure of household income. We use round 61 (2004/05, before treatment) and round 64 (2007/08, after treatment) data from the NSSEUS. The dependent variable is log real monthly consumption expenditure per capita. The MPCE is calculated by dividing monthly household consumer expenditures by household size. MPCE is deflated using the India-level monthly average price index for agricultural laborers from the Indian Labor Bureau. Column (1) of Table 7 presents the impact of MGNREGA on the monthly consumption spending of rural households per capita. The coefficient on the treatment impact does not differ statistically from zero. Varman and Kumar (2020), using different data from the India Human Development Survey (IHDS) shows an increase in monthly per capita consumption expenditure by MGNREGA participating households. In our context, the null effect of MGNREGA on monthly consumption spending in rural households may be because we do not directly observe participating households.

6.3. Changes in female labor market participation, financial autonomy, and bargaining power

Next, we explore changes in female labor market participation (Table 6) and earnings (Column (2) of Table 7) that resulted from MGNREGA. We test the effect of MGNREGA on the number of days worked, unemployed and not in labor force. We find a net positive impact on the number of days spent unemployed. This unemployment outcome for women is a bit confusing, although not inconsistent with the increase in labor market participation itself.

Much of the employment in India is self-employment and there is evidence showing that MGNREGA crowds out possibility of potential self-employment. Setting up of long-term self-employment has high transactional costs and individuals can delay this because of short-term employment opportunities offered by MGNREGA. We show an increase in the non-agricultural private female labor force and a net increase in the number of jobs in demand by women.

Casual individual earnings are available in the NSSEUS dataset. We use round 61 (2004/05, before treatment) and round 64 (2007/08, after treatment) data from the NSSEUS. Column (2) of Table 7 reports the impact of MGNREGA on married women's daily casual earnings. It is worth noting that a majority of employed people in India are self-employed, and therefore do not report wages in our data. The dependent variable is log of daily wage rate. The daily wage rate is calculated by dividing the casual earnings and the number of days worked in the last 7 days at the time of the survey. For our purposes, we only include married working individuals in our sample in column (2) of Table 7. because, as already mentioned, contraception information is only available for married women. The results suggest that, on average, the daily wage rate for married women rose by 6.5% after MGNREGA was introduced.

Table 6. Effect of MGNREGA on women's labor market outcomes

	Self-employed: Farm	Self-employed: Non-Farm	Public Laborer	Private Laborer: Farm	Private Laborer: Non-Farm	Unemployed: Sought work	Unemployed: did not seek work	Unpaid Family Labor	Not in Labor force
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
MGNREGA X Post x Female	0.012	0.004	-0.001	0.007	-0.005	-0.011***	0.000	0.002	-0.009
	(0.013)	(0.005)	(0.001)	(0.009)	(0.004)	(0.004)	(0.001)	(0.007)	(0.016)

MGNREG	-0.006	-0.007	0.002	-0.004	0.009***	0.009**	0.000	0.007	-0.018
A x Post	(0.012)	(0.006)	(0.002)	(0.008)	(0.004)	(0.004)	(0.001)	(0.011)	(0.011)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. variable	0.113	0.053	0.002	0.060	0.029	0.030	0.005	0.105	0.258
SD dep. variable	0.272	0.201	0.041	0.201	0.147	0.142	0.055	0.261	0.382
Observations	429120	429120	429120	429120	429120	429120	429120	429120	429120
R-squared	0.111	0.050	0.019	0.067	0.042	0.036	0.021	0.043	0.283

Notes:
[1] The dependent variable is the share of employment and unemployment at the district-year-quarter triplets. Inverse Hyperbolic transformation is applied to all dependent variables. The share of each employment is calculated as the ratio between the number of days spent in each employment in the last 7 days at the time of survey and the total number of days, 7.
[2] Individual controls include dummy variables for education levels (higher secondary and above), religion (Hindu), caste (scheduled castes and tribes, and other backward castes) and age.
[3] We use round 61 (2004/05, before treatment) and round 64 (2007/08, after treatment) data from the National Sample Survey (NSS) for Employment and Unemployment Situations in India. Post is a dummy variable indicating that observation is from the round 64 (2007/08).
[4] The sample is restricted to common support. The sample is also restricted to rural areas and individuals aged 18 to 59.
[5] WLS estimator is used for all regressions using IP-weights. Robust standard errors in parentheses are clustered at the district level.
[6] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

6.4. Composition and selection effects

According to the 2011 Census data, the migration rate in rural areas is 26.5%, while employment-related reasons account for 10.8% of individuals migration. Working-age men in villages often migrate to major cities[25] for most of the year and only return to their villages for short periods of time during festivals and as a result, women may not need to use temporary contraceptive methods. However, according to round 3 of DLHS (2007-2008), fewer than 1.5% of rural married women reported not using contraceptives because their husbands were away from the village to work or seek employment.

The NSS data for employment and unemployment includes the migration module for just two years: 1999-2000 and 2007-2008. In the 1999-2000 NSS survey, the question was asked whether people have moved away from the village for 60 days or more within the last 365 days to find work. The 2007-2008 NSS asks whether people moved from the village for one month or more, but less than six months within the last 365 days to find work. We use this question to construct the dummy variable for the short-term out-migration. We then use the DID technique using NSS 1999-2000 (pre-treatment period) and NSS 2007-2008 (post-treatment period) to estimate the effect of MGNREGA on the short-term out-migration.[26] Column (3) of Table 7 shows the impact of MGNREGA on short-term job search migration. On average, 2% of people aged 18 to 59 left the village temporarily last year to find work, suggesting that MGNREGA facilitates migration.

From a labor market perspective, the shift from agricultural to non-agricultural activities may affect contraceptives. There is evidence in the literature of a connection between fertility and agriculture, the rural agricultural population has high fertility in low- and middle-income countries. Using the NSS for the employment and unemployment dataset, we test this compositional effect (transition from agriculture to non-agriculture). The treatment effect (MGNERGA x Post) has a negative sign on the coefficient representing farming and a positive sign representing non-farming activities, although none of them is statistically significant.

Table 7. The impact of MGNREGA on monthly consumption expenditure per capita, daily wages for married women, and short-term migration in search of employment.

	Log (MPCE)	Log (Daily wage rate)	Migrate for job search
	[1]	[2]	[3]
MGNREGA x Post x Female		0.065*	
		(0.035)	

MGNREGA x Post	-0.004	-0.017	0.019***
	(0.026)	(0.030)	(0.007)
District FEs	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes
Mean dependent variable	5.110	3.027	0.037
SD dependent variable	0.469	0.787	0.176
Observations	429,120	66,075	392,298
Number of districts	483	483	488
R-square	0.344	0.550	0.056

Notes:
[1] The dependent variable in column (1) is log deflated monthly consumption expenditure per capita (MPCE). The MPCE is calculated by dividing monthly household consumer expenditures by household size. MPCE is deflated using the India-level monthly average price index for agricultural laborers from the Indian Labor Bureau.
[2] The dependent variable in column (2) is log of daily wage rate. The daily wage rate is calculated by dividing the casual earnings and the number of days worked in the last 7 days at the time of the survey. Casual earnings are deflated using the India-level monthly average price index for agricultural laborers from the Indian Labor Bureau.
[3] The binary dependent variable in column (3) is the inverse hyperbolic sine transformation of people who have moved away from the village in the last 365 days for employment or job search.
[4] Individual controls include dummy variables for education levels (higher secondary and above), religion (Hindu), caste (scheduled caste and tribes, other backward caste) and age.
[5] For columns (1) and (2), we use round 61 (2004/05, before treatment) and round 64 (2007/08, after treatment) data from the National Sample Survey (NSS) for Employment and Unemployment Situations in India. Post is a dummy variable indicating that observation is from the round 64 (2007/08). We exclude MGNREGA participants. Furthermore, in column (2), we limit the sample size to only married individuals whose wages are observed in the data (this excludes women who do not work or are self-employed).
[6] For column (3), we use the migration module from rounds 55 (1999/00, before treatment) and 64 (2007/08, after treatment) of the National Sample Survey (NSS) on Employment and Unemployment Situations in India. Post is a dummy variable indicating that observation is from the round 64 (2007/08).
[7] The sample is restricted to common support. The sample is also restricted to rural areas and individuals aged 18 to 59.
[8] WLS estimator is used for all regressions using IP-weights. Robust standard errors in parentheses are clustered at the district level.
[9] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

To sum up, we find empirical evidence that is consistent with our hypothesized pathways. First, MGNREGA through changes in labor market participation, in particular, we find that women have found off-farm paid work and that unemployment among women looking for

work during our study period has decreased. This change in women's labor market participation may have had an impact on household income. However, unlike other studies, we found no effect on the impact of treatment on monthly consumption expenditure for rural households. Second, we explored the impact of MGNREGA on women's earnings and found an increase in the daily wage rate for our sample. This supports our pathway that suggests that women who work for cash contribute to the total household income, and an increased in women's income leads to higher levels of autonomy within a household and therefore bargaining power in safer sexual relations with husbands. Third, MGNERGA has facilitated short-term migration, which suggests that husbands who are away from home in search of employment may have changed the need for women to use contraceptives.

7. Discussion and conclusion

This paper examines the impact that workfare programs have on family planning decisions within households. Exploiting the rollout of MGNREGA at the district level within a difference-in-difference model, we document that MGNREGA increased the use of family planning methods by 1.8 percentage points (3.2% increase over the sample mean) among married women across all age and wealth groups. This has important economic consequences because it allows women to remain in the labor market and/or change the number of children they have. Women's average age at first birth increased by 1.3 months from the sample mean of 19.36 years with the introduction of MGNREGA. Therefore, the ability to acquire modern methods of contraceptives can result in fewer births for women in their lifetime. Overall, the results of the paper provide new evidence and inform policymakers about the impact of MGNREGA on women's family planning methods.

One contribution of our article is to offer a connection between work programs and family planning decisions. The link between workfare and family planning decisions includes changes in female participation in the labor market, financial autonomy, higher earnings for women, and improved bargaining power. In addition, there are variations in short-term migration patterns for men that may affect the use of contraception. This study contributes to the literature that demonstrates that providing women with opportunities to generate income affects household reproductive decision-making. Increased family planning methods could address maternal morbidity and reduce negative impacts on child health in rural areas in low- and middle-income countries (Miller 2010).

A key limitation of this study is related to various sources of measurement error. First, reporting on contraceptive use might be inaccurate. That may arise because in traditional societies such as rural India, the discussion of sex and sex-related subjects is regarded as taboo. Second, our study includes only currently married women in the sample that may bias downward the prevalence of contraceptives. Third, the cultural setting also influences the reproductive decision-making along with the position of individual women (Gage 1995). Therefore, any detailed examination of contraceptive practice requires variables on cultural practices and social norms which are missing in the national datasets including DLHS. However, as long as the cultural practices and social norms are not changing over the short-run within a district, the use of district fixed effects (included in equations 1, 2, and 3), which takes into account time-invariant differences across districts, should be able to address any differences in culture. Finally, we recognize the short time span between MGNREGA implementation and our post-treatment observations.

Nevertheless, we demonstrate that providing job opportunities through a workfare program that includes women's employment increases the use of family planning methods. Contraceptive use increases and we find a small change in families' attitudes towards modern contraceptives. Our findings are robust to several specifications. These results contribute to our understanding of workfare programs, labor markets, and contraceptive use.

The yearly cost of work guarantee programs like MGNREGA is enormous for low-income countries such as India. MGNREGA competes with other Indian social safety net programs. Therefore, given scarce public resources, a complete measure of program benefits and costs can inform policy choices. This paper points out a positive unintended consequence of MGNREGA, which is the uptake of family planning methods in rural areas. Our findings confirm that increasing women's work opportunities leads to increased use of contraceptives. Therefore, in low- and middle-income countries, job guarantee programs can be viewed as complementary to family planning programs.

References

Ajefu, Joseph Boniface, and Olukorede Abiona. 2019. "Impact of Shocks on Labour and Schooling Outcomes and the Role of Public Work Programmes in Rural India." *The Journal of Development Studies* 55 (6): 1140–57.

Allan, Victoria, Sreeram V Ramagopalan, Jack Mardekian, Aaron Jenkins, Xiaoyan Li, Xianying Pan, and Xuemei Luo. 2020. "Propensity Score Matching and Inverse Probability of Treatment Weighting to Address Confounding by Indication in Comparative Effectiveness Research of Oral Anticoagulants." *Journal of Comparative Effectiveness Research* 9 (9): 603–14.

Anderson, Siwan, and Mukesh Eswaran. 2009. "What Determines Female Autonomy? Evidence from Bangladesh." *Journal of Development Economics* 90 (2): 179–91.

Asher, Sam, Tobias Lunt, Ryu Matsuura, and Paul Novosad. 2021. "Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India Using the SHRUG Open Data Platform."

Ashraf, Nava, Erica Field, and Jean Lee. 2014. "Household Bargaining and Excess Fertility: An Experimental Study in Zambia." *American Economic Review* 104 (7): 2210–37.

Azam, Mehtabul. 2011. "The Impact of Indian Job Guarantee Scheme on Labor Market Outcomes: Evidence from a Natural Experiment." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1941959.

Berg, Erlend, Sambit Bhattacharyya, D. Rajasekhar, and R. Manjula. 2018. "Can Public Works Increase Equilibrium Wages? Evidence from India's National Rural Employment Guarantee." *World Development* 103 (March):239–54. https://doi.org/10.1016/j.worlddev.2017.10.027.

Blackwell, Matthew, Stefano Iacus, Gary King, and Giuseppe Porro. 2009. "Cem: Coarsened Exact Matching in Stata." *The Stata Journal: Promoting Communications on Statistics and Stata* 9 (4): 524–46. https://doi.org/10.1177/1536867X0900900402.

Canning, David, and T Paul Schultz. 2012. "The Economic Consequences of Reproductive Health and Family Planning." *The Lancet* 380 (9837): 165–71.

Chari, Amalavoyal V, Peter Glick, Edward Okeke, and Sinduja V Srinivasan. 2019. "Workfare and Infant Health: Evidence from India's Public Works Program." *Journal of Development Economics* 138:116–34.

Chatterjee, Jagori, and Joshua D Merfeld. 2021. “Protecting Girls from Droughts with Social Safety Nets.” *World Development* 147:105624.

Cleland, John, Stan Bernstein, Alex Ezeh, Anibal Faundes, Anna Glasier, and Jolene Innis. 2006. “Family Planning: The Unfinished Agenda.” *The Lancet* 368 (9549): 1810–27.

Dasgupta, Aparajita. 2017. “Can the Major Public Works Policy Buffer Negative Shocks in Early Childhood? Evidence from Andhra Pradesh, India.” *Economic Development and Cultural Change* 65 (4): 767–804.

Deininger, Klaus, and Bart Minten. 2002. “Determinants of Deforestation and the Economics of Protection: An Application to Mexico.” *American Journal of Agricultural Economics* 84 (4): 943–60. https://doi.org/10.1111/1467-8276.00359.

D’Exelle, Ben, and Charlotte Ringdal. 2022. “Women’s Use of Family Planning Services: An Experiment on the Husband’s Involvement.” *Journal of Development Economics* 158 (September):102915. https://doi.org/10.1016/j.jdeveco.2022.102915.

Fetzer, Thiemo. 2020. “Can Workfare Programs Moderate Conflict? Evidence from India.” *Journal of the European Economic Association* 18 (6): 3337–75.

Gage, Anastasia J. 1995. “Women’s Socioeconomic Position and Contraceptive Behavior in Togo.” *Studies in Family Planning*, 264–77.

Gazeaud, Jules, and Victor Stephane. 2020. “Productive Workfare? Evidence from Ethiopia’s Productive Safety Net Program.” *American Journal of Agricultural Economics*.

Gehrke, Esther. 2019. “An Employment Guarantee as Risk Insurance? Assessing the Effects of the NREGS on Agricultural Production Decisions.” *The World Bank Economic Review* 33 (2): 413–35.

Hirano, Keisuke, Guido W Imbens, and Geert Ridder. 2003. “Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score.” *Econometrica* 71 (4): 1161–89.

Hogan, Dennis P, Betemariam Berhanu, and Assefa Hailemariam. 1999. “Household Organization, Women’s Autonomy, and Contraceptive Behavior in Southern Ethiopia.” *Studies in Family Planning* 30 (4): 302–14.

Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. “Causal Inference without Balance Checking: Coarsened Exact Matching.” *Political Analysis* 20 (1): 1–24. https://doi.org/10.1093/pan/mpr013.

Imbert, Clément, and John Papp. 2015. “Labor Market Effects of Social Programs: Evidence from India’s Employment Guarantee.” *American Economic Journal: Applied Economics* 7 (2): 233–63. https://doi.org/10.1257/app.20130401.

Jensen, Robert. 2012. “Do Labor Market Opportunities Affect Young Women’s Work and Family Decisions? Experimental Evidence from India.” *The Quarterly Journal of Economics* 127 (2): 753–92.

Joshi, Shareen, and T Paul Schultz. 2013. “Family Planning and Women’s and Children’s Health: Long-Term Consequences of an Outreach Program in Matlab, Bangladesh.” *Demography* 50 (1): 149–80.

Karra, Mahesh, Dan Maggio, Muqi Guo, Bagrey Ngwira, and David Canning. 2022. “The Causal Effect of a Family Planning Intervention on Women’s Contraceptive Use and Birth Spacing.” *Proceedings of the National Academy of Sciences* 119 (22): e2200279119.

Lahoti, Rahul, and Hema Swaminathan. 2016. “Economic Development and Women’s Labor Force Participation in India.” *Feminist Economics* 22 (2): 168–95. https://doi.org/10.1080/13545701.2015.1066022.

Maxwell, Lauren, Karen Devries, Danielle Zionts, Jeanne L Alhusen, and Jacquelyn Campbell. 2015. “Estimating the Effect of Intimate Partner Violence on Women’s Use of Contraception: A Systematic Review and Meta-Analysis.” *PloS One* 10 (2): e0118234.

McCarthy, Aine Seitz. 2019. “Intimate Partner Violence and Family Planning Decisions: Experimental Evidence from Rural Tanzania.” *World Development* 114:156–74.

Merfeld, Joshua D. 2019. “Spatially Heterogeneous Effects of a Public Works Program.” *Journal of Development Economics* 136:151–67.

———. 2020. “Moving Up or Just Surviving? Nonfarm Self-Employment in India.” *American Journal of Agricultural Economics* 102 (1): 32–53.

Miller, Grant. 2010. “Contraception as Development? New Evidence from Family Planning in Colombia.” *The Economic Journal* 120 (545): 709–36.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2017. “General Equilibrium Effects of (Improving) Public Employment Programs: Experimental Evidence from India.” National Bureau of Economic Research.

Palamuleni, Martin E. 2013. “Socio-Economic and Demographic Factors Affecting Contraceptive Use in Malawi.” *African Journal of Reproductive Health* 17 (3): 91–104.

Rani, S Indira, T Arulalan, John P George, EN Rajagopal, Richard Renshaw, Adam Maycock, Dale M Barker, and M Rajeevan. 2021. “IMDAA: High-Resolution Satellite-Era Reanalysis for the Indian Monsoon Region.” *Journal of Climate* 34 (12): 5109–33.

Ravallion, Martin. 1991. “REACHING THE RURAL POOR THROUGH PUBLIC EMPLOYMENT: Arguments, Evidence, and Lessons from South Asia.” *The World Bank Research Observer* 6 (2): 153–75. https://doi.org/10.1093/wbro/6.2.153.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. 2007. “Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California.” *Climatic Change* 81 (1): 19–38. https://doi.org/10.1007/s10584-005-9008-z.

Shah, Mihir, Neelakshi Mann, Varad Pande, and others. 2015. “MGNREGA Sameeksha: An Anthology of Research Studies on the Mahatma Gandhi National Rural Employment Guarantee (2005) Act 2006-2012.”

Stephenson, Rob, Apoorva Jadhav, and Michelle Hindin. 2013. “Physical Domestic Violence and Subsequent Contraceptive Adoption among Women in Rural India.” *Journal of Interpersonal Violence* 28 (5): 1020–39.

Sukhtankar, Sandip and others. 2016. “India’s National Rural Employment Guarantee Scheme: What Do We Really Know about the World’s Largest Workfare Program?” In *India Policy Forum*, 13:2009–10.

United-Nations. 2022. “Department of Economic and Social Affairs, Population Division.” *World Contraceptive Use* 2022.

Van den Broeck, Goedele. 2020. “Women’s Employment and Family Planning in Rural Uganda.” *Women & Health* 60 (5): 517–33.

Varman, P Mahendra, and Neeraj Kumar. 2020. “Impact of MGNREGA on Consumption Expenditure of Households.” *Economic & Political Weekly* 55 (39): 49–54.

Varshney, Deepak, Deepti Goel, and JV Meenakshi. 2018. “The Impact of MGNREGA on Agricultural Outcomes and the Rural Labour Market: A Matched DID Approach.” *The Indian Journal of Labour Economics* 61 (4): 589–621.

Westeneng, Judith, and Ben d’Exelle. 2015. “How Economic Empowerment Reduces Women’s Reproductive Health Vulnerability in Tanzania.” *The Journal of Development Studies* 51 (11): 1459–74.

Zimmermann, Laura. 2012. “Labor Market Impacts of a Large-Scale Public Works Program: Evidence from the Indian Employment Guarantee Scheme.” *IZA Discussion Paper*.

Appendix A: Additional Tables

Table A1. District-level variables

Variable	Source
Total Population	2001 Census
Percent rural	2001 Census
Area (in square km)	2001 Census
Percent Scheduled Castes	2001 Census
Percent Scheduled Tribes	2001 Census
Percent Literate	2001 Census
Average monthly per capita consumption expenditure	2004/05 NSSEUS
Average casual wage (2004/05 prices)	2004/05 NSSEUS
Labor force participation rate	2004/05 NSSEUS
Female labor force participation rate	2004/05 NSSEUS
Rainfall (2004)	NCMRWF
Growing degree days (2004)	NCMRWF

Note: We use the socioeconomic high-resolution rural-urban geographic platform for India (SHRUG) to construct 2001 census variables (Asher et al. 2021). NSSEUS refer to the National Sample Surveys on Employment and Unemployment Situation in India. NCMRWF refer to the National Centre for Medium Range Weather Forecasting (Rani et al. 2021). We use growing season (June through September) in a given year to construct rainfall and growing degree days.

Table A2. Individual summary statistics before matching

	Pre-Program (2002-2004)		
	Treated	Control	Diff. (p-val.)
Outcomes			
Any family planning methods	0.500	0.589	0.000
	(0.500)	(0.492)	
Any modern methods	0.428	0.512	0.000
	(0.495)	(0.499)	
Any traditional methods	0.072	0.077	0.506
	(0.259)	(0.267)	
Among women who are currently taking contraceptives			
Female sterilization	0.681	0.660	0.321
	(0.466)	(0.474)	
Male sterilization	0.022	0.018	0.378
	(0.148)	(0.135)	
Intrauterine Devices (IUDs)	0.022	0.045	0.000
	(0.147)	(0.208)	
Oral pills	0.075	0.063	0.134
	(0.263)	(0.242)	
Condom	0.051	0.079	0.000
	(0.220)	(0.270)	
Rhythm/Periodic abstinence/Withdrawal	0.126	0.125	0.901
	(0.332)	(0.330)	
Individual-level characteristics			
Women age in years	30.169	30.708	0.000
	(7.296)	(7.201)	
Women can read or write	0.388	0.489	0.000
	(0.487)	(0.499)	
Spouse can read or write	0.650	0.738	0.000
	(0.477)	(0.440)	
Number of children	2.743	2.653	0.013
	(1.723)	(1.630)	
Household-level characteristics			
Religion: Hindu	0.824	0.764	0.021
	(0.381)	(0.424)	
Scheduled Castes/Tribes	0.396	0.317	0.000
	(0.489)	(0.465)	

Note: Standard deviations are in parentheses. Treated includes phase one and two districts, and control includes phase three districts. The third column, the difference, is computed using OLS regressions and standard errors clustered at the district level. Source: DLHS round 2 (2002-2004).

Table A3. Logistic regression predicting treatment

	Treatment
Total Population	1.000***
	(0.000)
Percent rural	186.748***
	(7.485)
Area (in square km)	1.000***
	(0.000)
Percent Scheduled Castes	1905.793***
	(111.530)
Percent Scheduled Tribes	123.363***
	(2.849)
Percent Literate	0.074***
	(0.003)
Average MPCE	0.999***
	(0.000)
Average casual wage	0.995***
	(0.000)
Labor force participation rate	0.030***
	(0.002)
Female labor force participation rate	8.851***
	(0.657)
Rainfall (mm)	1.000***
	(0.000)
Growing degree days	1.000***
	(0.000)
Observations	631,152

Note: Standard errors are in parentheses. Odds ratios are reported.

Table A4. Effect of MGNREGA on the use of family planning methods – Placebo

	Any methods [1]	Any modern methods [2]	Any traditional methods [3]
MGNREGA x Post	-0.011	-0.012	0.001
	(0.011)	(0.008)	(0.007)
District FEs	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes
Interview month-year FEs	Yes	Yes	Yes
Mean dependent variable	0.484	0.422	0.062
SD dependent variable	0.500	0.494	0.241
Observations	549,059	549,059	549,059
Number of districts	422	422	422
R-square	0.150	0.146	0.097

Notes:
[1] The binary dependent variables indicate whether a married woman uses any family planning methods in column (1), any modern methods in column (2), and any traditional methods in column (3).
[2] The term 'any methods' refers to individuals currently using family planning methods. Modern methods include sterilization of women and men, using IUDs/copper-t/loop, oral pills, male and female condoms, and other modern methods. Traditional methods include using rhythm, periodically abstaining, withdrawing, and other methods.
[3] For our falsification test, we use round 1 of DLHS (1998/99) as the pre-program and round 2 of DLHS (2002/04) as the post-program. MGNREGA is a dummy variable, 1 for district that has implemented the workfare program. Post is a dummy variable that indicates that the observation is from the 2002/04 round of DLHS.
[4] The sample is limited to common support.
[5] WLS estimator is used for all regressions using IP-weights. Robust standard errors in parentheses are clustered at the level of treatment (district).
[6] Levels of significance: $p<0.01^{***}$, $p<0.05^{**}$, $p<0.10^{*}$.

Appendix Figures

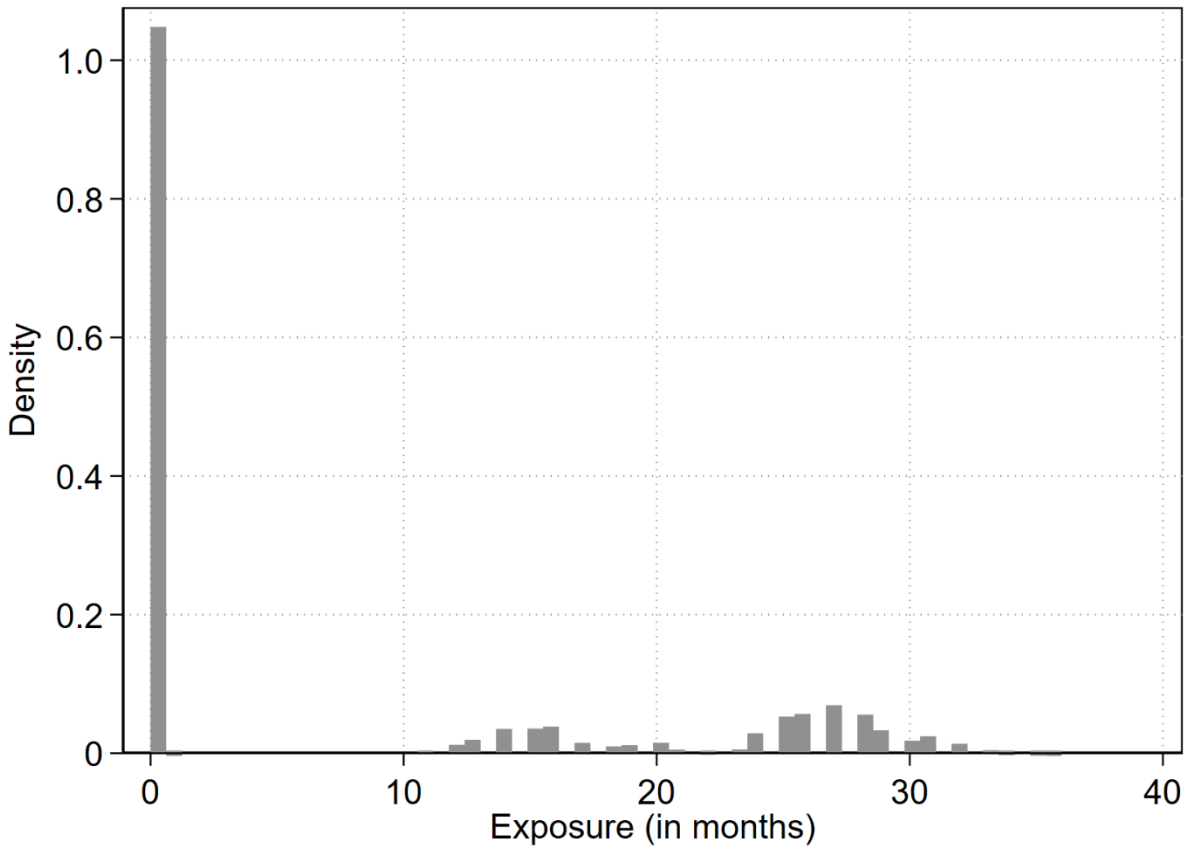

Figure A1. Distribution of exposure in months.

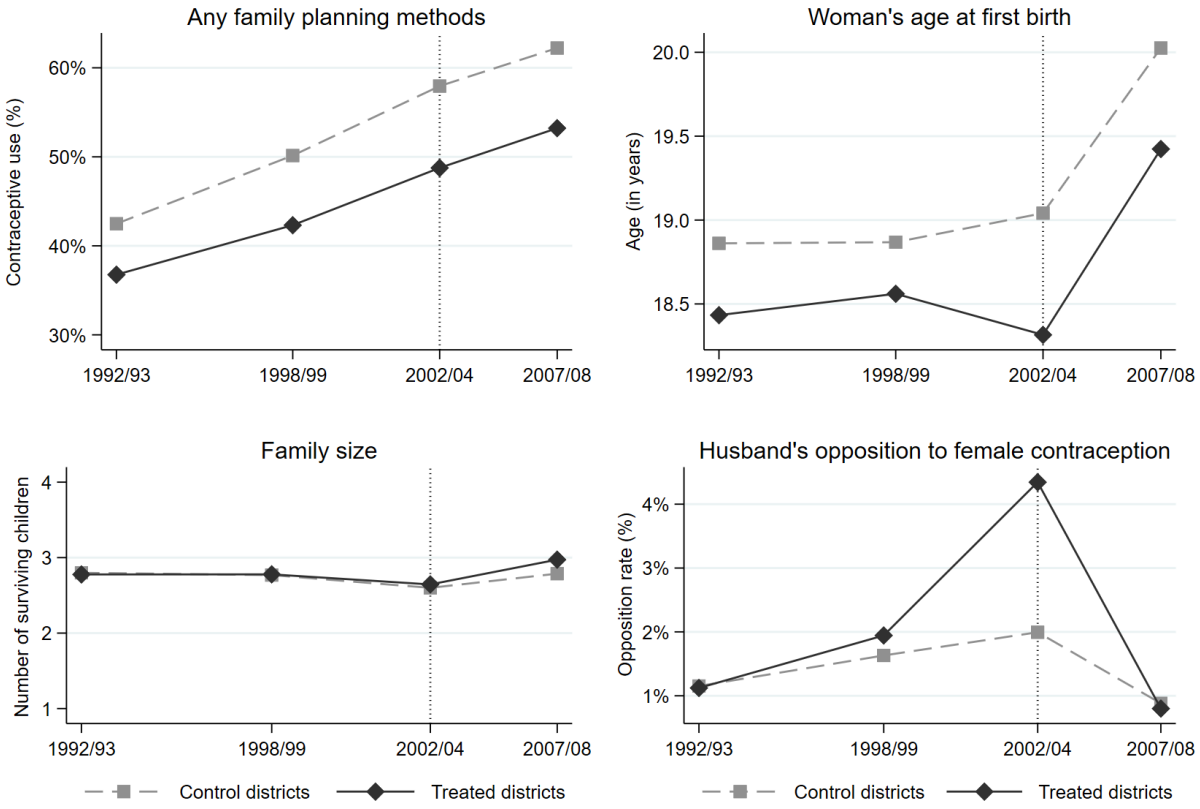

Figure A2. Pre program trends in the outcome of interest: any family planning methods (upper left), woman's age at first birth (upper right), family size (bottom left), and husband's (and other family members) opposition to female contraception (bottom right).

Note: The y-axis measures the average means from the pre program: DHS rounds (1992/93 and 1998/99) and DLHS-2 (2002/04) and post-program: DLHS-3 (2007/08).

[1] Data are available at https://www.un.org/development/desa/pd/data/world-contraceptive-use
[2] In the past, developing countries have used public workfare programs to lift poor people out of poverty. For example, the Maharashtra Employment Guarantee Scheme in India, 1975-89, and Food for Work Program in Bangladesh, 1987-88, have provided major relief in response to drought and famine (Ravallion 1991)
[3] See (Sukhtankar and others 2016) for a synthesis of the literature on MGNREGA.
[4] The program was renamed the Mahatma Gandhi National Rural Employment Guarantee Act in 2009.
[5] In 2012, the Government of India, mandated that MGNREGA wages be deposited directly to the bank accounts of workers to avoid corruption and leakages. Available at https://nrega.nic.in/Circular_Archive/archive/Operational_guidelines_4thEdition_eng_2013.pdf
[6] Other conditions include a. The adult members of each household who live in rural areas and are willing to do unskilled manual labor may submit their names, age and household address to the village governing body (Gram Panchayat) at the village level for the issue of a job card. b. Each adult member who has a job card is guaranteed employment for up to 100 days in a given fiscal year within 15 days of the request for work. c. A minimum of 14 days of continuous employment with no more than 6 days per week.
[7] Available at https://rural.nic.in/en/press-release/participation-rural-women-mgnregs
[8] Available at https://nrega.nic.in/Circular_Archive/archive/MGNREGA_SAMEEKSHA.pdf
[9] More information about the DLHS sample selection is obtained at rchiips.org
[10] DLHS-2 reference period is from January, 1999-2001 to survey date and DLHS-3 reference period is from January 2004 to survey date. Since MGNREGA was introduced post-2005, there may be a concern when a woman's age at first birth is examined as an outcome. For example, if a woman was asked their age at first birth for a child born during the reference period, some of which was before MGNREGA, a child born pre-MGNREGA could count as part of the post-treatment group. Since we do not observe children's ages in the third survey round, we cannot limit the sample to consider only children born after MGNREGA implementation. Our results for woman's age at first birth represent lower bounds due to this.

[11] We do not include the first round of the DLHS dataset in main specification. The first round took place from 1998 to 1999. From 1998 to 2008, many districts and state geographical boundaries changed. Single districts were divided into multiple districts and hence, assigning treatment and control groups becomes difficult. However, at the cost of dropping districts that were split, we include the first round of DLHS in both the placebo test and event-study regression. Where it is not possible to use the first round of DLHS, we use the Demographic and Health Survey round conducted in 1998/99. Furthermore, identifying covariates in the first round of the DLHS dataset is difficult. DLHS-4, collected in 2012-2013, excludes 9 major states, such as Bihar, Jharkhand, Uttar Pradesh, Uttarakhand, Madhya Pradesh, Chhattisgarh, Orissa, Rajasthan and Assam from its survey, and hence is not comparable with DLHS-3. Therefore, we use only DLHS-2 as the pre-treatment period and DLHS-3 as the post treatment period.

[12] We follow literature to calculate the growing degree days, with the lower and upper temperature thresholds equal to 8 and 32 degrees Celsius, respectively.
[13] The DLHS-3 recorded that 3.3% of contraceptive users faced difficulties in getting any methods in treatment districts, and 2.5% in control districts.
[14] Scheduled castes or tribes represent the groups of marginalized castes in Indian society.
[15] We also investigate heterogeneous effects that are based on age, wealth, the percentage of agricultural workers, lean and peak agricultural seasons, education level, castes and tribes. Interestingly, there were no statistical differences in impacts at different levels of these variables. The results are available upon request.
[16] DLHS also provides survey sample weights. The results are unchanged when we use the DLHS survey weights for estimation of the treatment effects (Column 2 of Table 5).
[17] The weights are generated as follows: 1/propensity score for the treated group and 1/ (1-propensity score) for the control group.
[18] About 10% of data is excluded when restricted to common support.
[19] 49,253 observations are missing for the woman's age at first birth age, which indicates that she has not yet given birth to a child.
[20] Not all women with children in the sample had the option to change their age at the time of their first child's birth (if their first child was born before MGNREGA). Since we do not observe children's ages in the third survey round, we cannot limit the sample to those that had the choice.

[21] In treated districts, 11% of husbands opposed contraceptive use, while in control districts, 12% opposed. 0.6% of women in both the treated and control districts said that other family members opposed the use of contraceptives.
[22] The calculation is as follows: contraceptive use (100*(0.001/0.56) *12 = 2.14) and woman's age at first birth (100*(0.01/19.34) *12 = 0.619).
[23] We used the cem Stata package to calculate weights, and these weights were used in a simple weighted regression (Blackwell et al. 2009).
[24] Star states include Andhra Pradesh, Himachal Pradesh, Madhya Pradesh, Chhattisgarh, Rajasthan, Uttarakhand, and Tamil Nadu.
[25] According to Census 2011 data, the migration rate in rural areas is 26.55%. Employment-related reasons account for 10.8% of individuals' migration.