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Spilling Over

The Benefits of Public Works Projects for Groundwater in India

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Abstract

Depletion of groundwater is a major challenge in India. This paper examines how a major rural public works program (Mahatma Gandhi National Rural Employment Guarantee Act of 2005) that financed the construction of surface water infrastructure that may have plausibly increased aquifer recharge rates impacted groundwater levels. Using a difference-in-differences approach on the staggered and heterogeneous rollout of the program, the paper shows that groundwater levels increased after its implementation. These increases were concentrated in states that constructed the largest number of program-financed surface water projects. The observed increases in groundwater appear to have led to increases in the irrigated area of high-value crops and greater overall irrigation during the dry season.

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Spilling Over: The Benefits of Public Works Projects for Groundwater in India

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1 Introduction

Depletion of groundwater is a global crisis, which is especially true in India (Shapiro et al., 2018; Zaveri et al., 2016). Of the major groundwater aquifers in the arid and semi-arid areas of the world, those in northwestern India experienced the largest and fastest declines in water storage capacity from 2002 to 2013, with a total decline roughly double the other major arid and semi-arid aquifers (Famiglietti, 2014). Declining groundwater levels threaten the viability of irrigated agriculture in India (Zaveri et al., 2016), with at least 65% of Indian agricultural production occurring in states that are currently experiencing groundwater stress (Ryan and Sudarshan, 2020). Northwest India has one of the world's largest discrepancies between water intensity of crops and natural water availability (Carleton et al., 2023).

Recognizing the importance of groundwater and irrigation in Indian agriculture, the Indian government has attempted numerous policy programs to manage and mitigate groundwater withdrawals for irrigation. This goal has been the explicit purpose of some policy programs (e.g., the Atal Bhujal Yojana program) and an ancillary target of others, for example, the Mahatma Gandhi National Rural Employment Guarantee Act of 2005 (MNREGA). MNREGA was primarily a rural employment program intended to reduce poverty and rural unemployment, but it had a secondary goal of increasing rural infrastructure to enhance rural productivity. These infrastructure projects explicitly targeted the creation of durable public works projects that improved irrigation and water conservation. More than half of the initial funding - through 2009 - was for water-related projects (The World Bank, 2011).

In this paper, we examine the impact of MNREGA implementation on groundwater levels throughout India. Despite the large and growing body of literature on MNREGA, the extent to which it succeeded in providing useful, efficiency-enhancing assets remains unanswered (Sukhtankar, 2016). Examining the impact of MNREGA on groundwater levels provides an indirect test of its success in providing useful infrastructure. Improving irrigation, water conservation, and water storage should result in higher groundwater levels as these improvements allow for increased groundwater recharge. Examining MNREGA's impact on groundwater levels thus provides a test of the effectiveness of the infrastructure construction it financed without directly assessing the quality or completeness of individual projects.[1]

Assessing MNREGA's success or failure in raising groundwater levels also offers an equilibrium assessment of the impact of MNREGA water projects. All else equal, improving water conservation infrastructure should lead to higher levels of groundwater via higher rates of recharge. Thus, in partial equilibrium, if MNREGA succeeds in providing effective infrastructure, it should have resulted in higher groundwater levels. However, higher groundwater levels lower the cost of irrigating cropland. Thus farmers may have responded to higher groundwater levels caused by MNREGA

[1]We chose to study MNREGA, rather than one of the more targeted groundwater programs, because we are interested in understanding the relationship between large public welfare programs and environmental outcomes. There is a growing literature (e.g. Gertler et al. (2006); Alix-Garcia et al. (2013); Garg et al. (2020); Behrer (2023)) examining this relationship and, given the popularity of these types of programs in LMICs, it is important to understand their (often unintended) environmental consequences.

projects by increasing the area of irrigated cropland. That would put pressure on groundwater resources and result in declines in groundwater levels relative to the partial equilibrium response.

We examine which of these two effects dominate empirically using a difference-in-differences framework that takes advantage of the sequential roll-out and heterogeneous implementation of MNREGA across the country, coupled with data from more than 20,000 test wells that measure groundwater levels throughout India at multiple times each year from the late 1990s to 2012. We find evidence that suggests that MNREGA did succeed in improving rural, water-related infrastructure. MNREGA implementation appears to have raised groundwater levels (increased groundwater storage) immediately following the monsoon season and through the dry planting season. This is consistent with MNREGA projects improving recharge rates and allowing for more monsoon precipitation to reach and be stored in groundwater reservoirs.

Higher groundwater levels have meaningful consequences for Indian farmers. Total area irrigated increases after the implementation of MNREGA. More tellingly, the area irrigated by wells increases significantly after the implementation of MNREGA. This increase stands in contrast to no observed change in the area irrigated by canals, tanks, or "other sources" of irrigation water. Consistent with more irrigation water being available, we observe increases in the soil moisture level after the implementation of MNREGA. This effect is concentrated during the rabi (dry) season when soil moisture is most determined by irrigation levels. Likely as a consequence of the increased availability of irrigation water, we find that farmers substantially increase their irrigation of high-value, water intensive crops after the implementation of MNREGA. Overall our results suggest that MNREGA succeeded in improving the water conservation and irrigation infrastructure in states in which it was well-implemented. These improvements led to higher groundwater recharge rates that, in turn, made irrigation water more available for farmers and allowed them to increase irrigated areas and shift into higher value crops.

Our work speaks directly to a number of literatures. There is a large, and growing, body of work on the effectiveness of MNREGA as a policy project.[2] In addition to the commonly examined outcomes (e.g. wage impacts (Imbert and Papp, 2014)) a growing body of work examines the impact of MNREGA on a host of environmental outcomes (e.g. air pollution (Behrer, 2023) and resilience to droughts (Dasgupta, 2017)). We add to that literature by focusing on the impacts of MNREGA on groundwater levels, an issue of specific focus of MNREGA, and of general concern for Indian policymakers. Better managing India's groundwater and reducing stress on those resources has been a long-term goal of Indian policy (Mukherjee et al., 2015). Much of the existing work examining these efforts has focused on developing strategies to curtail extraction (Ryan and Sudarshan, 2020; Badiani and Jessoe, 2013). We provide evidence of how policy can increase recharge, and subsequently storage, providing another tool to combat declining water levels.

The rest of the paper is as follows. We briefly review the key details of the MNREGA program and the characteristics of India's groundwater resources in section 2 before describing our data and empirical approach in sections 3 and 4. We present results and discussion in section 5 and then

[2] There are too many papers to list individually here. For a comprehensive review see Sukhtankar (2016).

conclude.

2 Background

2.1 History of MNREGA

MNREGA is an anti-poverty program of the Government of India designed with two goals in mind. First, it was intended to provide employment to residents of rural districts of India who might have been under- or unemployed. Second, it was intended - using the labor of those residents of rural districts - to create public assets that "address causes of chronic poverty...so that the process of employment generation is on a sustainable basis" (GOI, 2007). A particular focus of the asset creation portion of the program was the creation of infrastructure that would aid in irrigation, water conservation, and drought-proofing communities.

Despite the stated intention of the program to create durable assets that increased rural productivity and reduced poverty, the focus of nearly all evaluations of MNREGA has been on human capital or labor-market related outcomes. The existing literature has broadly found that MNREGA led to increases in both local wages and employment on public projects (Zimmermann, 2020; Imbert and Papp, 2014; Merfeld, 2019; Berg et al., 2018), may have reduced migration (Imbert and Papp, 2015), likely improved health outcomes for rural residents (Thomas, 2015; Dasgupta, 2017; Nair et al., 2013), but reduced educational attainment for some students (Shah and Steinberg, 2015).

Evaluations of MNREGA's impact have also highlighted substantial variation in implementation quality across states (Sukhtankar, 2016). While MNREGA was financed by the Government of India, implementation of projects was conducted at a state and local level. This has led to large differences in the scope and quality of implementation across states (Muralidharan et al., 2016; The World Bank, 2011). In particular, Imbert and Papp (2014) show that nearly all the wage and employment impacts of MNREGA are concentrated in what they define as "Star states" or those where the fraction of time spent by prime-age adults working on public works projects after MNREGA was greater than 1%.[3]

More recent work has attempted to move beyond human capital-focused outcomes to examine the general equilibrium effects of MNREGA (Muralidharan et al., 2017). They find little evidence of a persistent impact of MNREGA projects on rural productivity. However, MNREGA's overall impact on rural productivity remains one of the major open questions (Sukhtankar, 2016). In particular, no study has measured the return on investment in asset creation or the quality of the assets created by MNREGA (The World Bank, 2011). By examining one potential consequence of improving water-related infrastructure – higher groundwater recharge rates – we aim to shed some light on the question of whether the assets created by MNREGA may have enhanced rural productivity by improving access to groundwater. By examining how farmers change planting decisions after groundwater levels change, we can also provide a lower bound estimate of the

[3]The "Star states" were Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Rajasthan, Tamil Nadu, and Uttarakhand.

potential benefits of these productivity improvements.

2.2 Indian groundwater

Most of India lies above aquifers that are classified as having "high" to "very high" rates of recharge, with rates greater than 100mm per year (Mukherjee et al., 2015). This includes nearly the entirety of India's bread basket in the northwest and across the Indo-Gangetic plain. These areas have aquifers that display a high degree of surface connectivity. In these regions, agriculture accounts for roughly 95% of the annual withdrawals from renewable groundwater resources (Mukherjee et al., 2015).

The high level of surface connectivity for many of India's aquifers is central to how surface-level MNREGA infrastructure projects could increase access to groundwater. Broadly, aquifers lie on a spectrum of connectivity between those, like in much of India, with high rates of annual recharge where water that falls on the surface can easily percolate through rocks and soil to reach them. These aquifers typically lie in river basins with gravel or sandy soils above an impermeable layer (i.e., clay) that traps and pools water which percolates down from the surface. At the other end of the connectivity spectrum are "fossil" aquifers that have no connectivity to the surface and were formed when water was trapped in a geological layer during past geological activity.

Aquifers with high surface connectivity can be recharged by capturing and pooling water on the surface and allowing it to percolate into the aquifer. This approach to recharging aquifers has been used around the world, with particular attention in California (Dahlke et al., 2018; Ulibarri et al., 2021). Construction of check dams, additional soft-bottomed irrigation canals, and soft-bottomed water "tanks" under MNREGA are all projects that may have led to increased aquifer recharge by allowing surface water to pool and then percolate through the soil to the aquifer.[4]

Because of the monsoonal weather pattern that ensures that the vast majority of precipitation in India falls during the wet season (typically June to September), access to groundwater is essential for much of the agriculture in India. Access to groundwater for irrigation facilitates the second of the two cropping seasons that occurs during the dry period of the year.[5] Of the irrigated cropland in India, groundwater accounts for nearly twice as much planted area as the next most common source of irrigation (canals) (Dhawan, 2017).

The importance of groundwater for Indian agriculture is underlined by two recent papers that find substantial reductions in welfare in areas that lose access to groundwater. Using variation induced by the geology underlying aquifers in Karnataka, Blakeslee et al. (2020) find that losing access to groundwater resources leads to a permanent decline in farm income and significant wealth losses. These losses induce some farmers to transition into manufacturing labor. These effects are driven by reductions in high-value horticulture and dry season cultivation.

Sekhri (2014) also uses variation in the underlying geology and depth to groundwater to examine

[4] For examples of these types of projects financed under MNREGA, see Figure A2.

[5] The planting seasons are kharif, typically June to October, and rabi, typically November or December to April or May.

how losing access to groundwater influences village-level outcomes. Wells deeper than 8m cannot use atmospheric pressure based pumps to extract water and therefore require more expensive mechanical pumps. This creates a clear threshold around water accessibility. Using this threshold, she shows that villages just below this threshold had poverty rates 9-10% higher than those just above and were 25% more likely to experience conflict over water. This builds on earlier work showing that a 1 meter increase in the depth to groundwater reduces food grain production by 9% and cash crop production by 5% (Sekhri et al., 2013).

3 Data

3.1 Water depth data

We collect data on groundwater levels from the Central Ground Water Board (CGWB) observation wells.[6] The CGWB monitors groundwater levels at nearly 23,000 monitoring stations across the country. Water depth data is collected in August (monsoon), November (kharif), January (rabi), and March/April/May (pre-monsoon), where the pre-monsoon collection times vary by state depending on the normal beginning of the monsoon (CGWB, 2021). On average, we have nearly 25 wells per seasons per district year. CGWB monitoring wells include a mix of open dug-wells and tube wells. Typically tube wells have a much deeper monitoring depth compared to dug wells.

3.2 Winter cropped area

We collect data on area planted in winter crops from NASA's Earth Observing System Data and Information System provided by the SEDAC center at Columbia University. This data provides a raster layer that indicates whether a pixel is planted in crops based on the peak Enhanced Vegetation Index value detected by the MODIS platform over the period October to March (Jain et al., 2017a,b). We aggregate the underlying 1-km pixel-level data to district level to determine the area of each district planted in winter crops in each year in the sample.

3.3 Meteorological data

We collect weather re-analysis data from ERA5. ERA5 is a weather re-analysis product produced by the European Commission's Copernicus Climate Change Service.[7] We use data from the ERA5 Land hourly product. This provides data at an hourly level on a grid of $0.1°\times0.1°$, which translates to a 9km resolution. We use data on temperature and precipitation over the full sample from 2003 to 2014. We aggregate these weather variables to the district level by averaging over all grid points that fall within a district boundary.

[6] Data accessed from: http://cgwb.gov.in/GW-data-access.html

[7] Data available here: https://cds.climate.copernicus.eu/cdsapp!/dataset/reanalysis-era5-land?tab=overview

3.4 Irrigation data & crop data

We use data on irrigation statistics from the ICRISAT District Level Data to examine farmers' responses to changes in the groundwater depth. The data provide information on areas irrigated by source: canals, tanks, tube wells, and other wells. We also access data on crop-wise irrigated areas for water-intensive crops.[8]

3.5 Soil moisture

We use data on soil moisture from the European Space Agency's Climate Change Initiative (Dorigo et al., 2017; Gruber et al., 2019).[9] This provides a gridded reanalysis product that uses satellite observation to estimate soil moisture (measured as m^3 of water per m^3 of soil). The ESA CCI SM algorithm combines active scatterometer data and the passive radiometer data to estimate the moisture content of the first few centimeters of the top soil. Environmental studies have shown soil moisture to be a good indicator of irrigation water use globally (Zohaib and Choi, 2020) and drought conditions in India (Modanesi et al., 2019). The data is provided on a $0.25° \times 0.25°$ grid. We aggregated to districts by averaging over all gridpoints within a district's boundaries.

4 Empirical Approach

In our primary empirical approach we take advantage of both the staggered roll-out of MNREGA and the heterogeneity in implementation to estimate a difference-in-differences model with a true control. Our approach is similar to that taken in García (2022) and relies on the fact that MNREGA implementation in non-Star states was limited compared to Star states to estimate the impact of MNREGA by comparing outcomes in Star and non-Star states after implementation.[10] This approach has the advantage of allowing for comparisons between Treated and Never Treated districts, which alleviates many of the most significant challenges with estimation in the staggered difference-in-differences approach (Goodman-Bacon, 2018; Callaway and Sant'Anna, 2021).

In Figure 1 we show the average number of water projects of various types completed in Star and non-Star states. Star states complete substantially more conservation, irrigation, and micro-irrigation projects than non-Star states.[11] They also complete slightly more drought mitigation projects and slightly fewer flood mitigation projects. Collectively Star states complete almost five times as many projects on average as non-Star states. These differences in the number of completed projects lend support to our choice to define treatment based on both the timing of MNREGA implementation and location in a Star state.

[8] Data available from ICRISAT: http://data.icrisat.org/dld/src/irrigation.html

[9] Data available here: https://esa-soilmoisture-cci.org/ We use data from ESA CCI SM v06.1

[10] In A1 we present results that use only the staggered roll-out of MNREGA for identification, an approach that is more standard in the literature on MNREGA. This approach has the disadvantage of not allowing for comparisons to a Never Treated control group because all districts eventually receive MNREGA. Broadly our results are consistent between the two approaches.

[11] Table A2 formally tests whether Star states complete more projects than non-Star states and confirms that they do.

Specifically, we estimate variations of the following base specification:

$$\text{Depth}_{iy} = \beta\Big(\mathbb{1}\big[\text{NREGA}_{iy}\big] \times \mathbb{1}\big[\text{Star}_i\big]\Big) + \psi\text{Precip}_{iy} + \omega\text{Precip}_{iy}^2 + \theta\text{Temp}_{iy} + \alpha_i + \chi_y + \eta_s + \epsilon_{iy} \quad (1)$$

where Depth_{iyq} is the inverse hyperbolic sine transformation of the average depth to groundwater in district i, year y, and season q.[12] Larger numbers indicate that wells must be deeper, and therefore more expensive, to reach groundwater. Depth measurements are taken during the monsoon, at the end of the kharif season, during the rabi season, and prior to the start of the monsoon. Our variable of interest is the interaction of $\mathbb{1}\big[\text{NREGA}_{iy}\big]$, an indicator for MNREGA presence in a district, and $\mathbb{1}\big[\text{Star}_i\big]$, an indicator for whether the district lies within a Star state. We include a quadratic in the total precipitation the district receives in a year and control for the average temperature in the district during the year. We also include district (α) and year (χ) fixed effects and a quadratic state $\times$ year (η) trend. We cluster standard errors at the district level (Abadie et al., 2017).[13]

Our primary outcome of interest is β, which provides (approximately) the percent change in depth to groundwater in Star states compared to non-Star states after implementation of MNREGA. Note the district fixed effects absorb the Star indicator so we only specify the interaction in Equation 1. The key assumption in our approach is that the trends in depth to groundwater in Star and non-Star states were parallel prior to the implementation of MNREGA and that these trends would have continued to evolve similarly absent the implementation of MNREGA.[14] The event studies for each of our outcomes suggest that the assumption of parallel pre-trends is met. That these trends would have continued to evolve in parallel absent MNREGA is fundamentally untestable.

In our primary approach we estimate Equation 1 using the approach described in Callaway and Sant'Anna (2021) using their provided Stata packages. To test for pre-trends we estimate event studies using the approach described in Borusyak et al. (2024) using their provided Stata packages.[15] In Appendix A1 we estimate a traditional staggered difference-in-differences that uses the full roll-out of MNREGA and show our results are broadly robust to this approach as well.

To examine farmers' response to any changes in groundwater levels due to MNREGA, we retain the right hand side of Equation 1 but replace the left hand side with the inverse hyperbolic sine of soil moisture and inverse hyperbolic sine of area irrigated from various different sources. We use the same specification to examine how the area of different crops that are irrigated changes after implementation of MNREGA. For these analyses we replace the left hand side with the inverse

[12] We use the IHS transformation to put our estimates in more easily interpretable percentage terms and limit the impact of outliers on our estimates. In results available upon request we show that all of our primary results are robust to using the un-transformed measures of depth to groundwater in meters or area irrigated in HA.

[13] As a very conservative test - because it reduces the number of clusters to only 21 - we can cluster errors at the state level instead of districts. Our results on kharif, rabi, and Pre-monsoon depth to groundwater remain robust to this clustering at the 5% level.

[14] Note that the difference-in-differences approach does not require balance on other observables between Star and non-Star states.

[15] In Appendix A4 we provide event studies estimated with the approach described in Callaway and Sant'Anna (2021) as a robustness check.

hyperbolic sine of the irrigated area planted in various different crops.

We assign treatment at the district, rather than sub-basin, level. It might seem more natural, given the connected nature of sub-basins, to conduct our analysis at the sub-basin level. But the unit of administration for groundwater management is the district (Bhogale and Khedgikar, 2022). The district is also the unit of treatment for MNREGA and the challenge of assigning MNREGA treatment at the sub-basin level does not have an obvious solution.[16] We discuss the implications of this choice for our estimates at length in Appendix A2 . The primary take-away from this discussion is that if one is concerned about within sub-basin spillovers, our estimates are likely to be a lower bound of the true effect.

5 Results & Discussion

5.1 NREGA's impact on depth to groundwater

We first present results from the event studies estimated for the depth to groundwater at each point in the year after the implementation of MNREGA. Shown in Figure 2 these event studies suggest that MNREGA led to a substantial reduction in the depth to ground-water across all seasons. We see little to no evidence of pre-trends in the depth to groundwater measured in any of the four seasons.[17]

Our difference-in-differences estimates in Table A1 indicate that after the implementation of MNREGA, the depth to groundwater declined by between 7% and 8% after the monsoon seasons and at the beginning of the kharif seasons.[18] We see even larger differences in depth to ground water for measurements taken at the start of the rabi season and prior to the monsoon, of between 11% and 15%. The increase in effect size from the monsoon and kharif seasons to the start of the rabi season may be a consequence of rainfall, that predominantly falls during the monsoon, stored in surface infrastructure having had more time to percolate into the aquifers by the start of the rabi season.

We can also examine the impact of MNREGA implementation using continuous measures for the number of each type of project a given state implemented. In Table A4 we show a continuous measure of the quality of MNREGA implementation - the cumulative total of conservation or irrigation projects completed - that yields similar results to our binary treatment indicator. An additional 100,000 completed conservation projects reduces depth to groundwater by between 4% and 6% depending on the season. Irrigation projects reduce depth to groundwater by a similar 4% to 7%.

[16] These problems are exacerbated by using smaller units of government administration, such as blocks or villages (e.g. Gulzar and Pasquale (2017)).

[17] We also test if districts in different phases of the MNREGA had significant differences in the number of groundwater extraction structures prior to the program. The Fourth Minor Irrigation Census conducted in 2006-07 provides a count of all dug wells and tube wells present in the country. Using these data, we do not detect significant differences in pre-program well characteristics (Table A3).

[18] These results and all of our subsequent difference-in-difference estimates are based on implementing the methodology described in Callaway and Sant'Anna (2021) using their Stata package `csdid`.

Our results are consistent with MNREGA projects improving recharge rates by improving water conservation and/or irrigation infrastructure. Because much of this infrastructure is constructed with unlined bottoms which therefore allows water to percolate from the surface into the groundwater it leads to recharge and raises groundwater levels. It also appears, given the decline in water levels from the beginning of the rabi season to the pre-monsoon measurements, that some of this is drawn down by farmers and used for irrigation.

We therefore turn now to the impacts on farmers' irrigation choices and direct measurements of soil moisture pre- and post-MNREGA implementation.

5.2 Impacts on irrigation

To test whether farmers take advantage of the increased water stored in aquifers implementation of MNREGA, we examine whether soil moisture increases after implementation of MNREGA, whether farmers increase the area of crops that are irrigated, and what sources are used for irrigation pre- and post-MNREGA. If the projects that were constructed due to MNREGA raised groundwater levels the reliability of access to groundwater should have been increased. To the extent that the cost of irrigation depends on the height the water needs to be raised, the cost of accessing that water would also have declined. A possible consequence of the increase in reliability and decrease in access costs is a transition in what farmers plant. In particular, access to more reliable and lower cost sources of groundwater typically lead farmers to adopt higher value and more water intensive crops (Hornbeck and Keskin, 2014, 2015).

Starting with soil moisture and using our satellite based measures, we show that soil moisture (measured as the quantity of water in a cubic meter of soil) increases after the implementation of MNREGA. The event studies (Figure 3) for both annual soil moisture and soil moisture during the rabi season show substantial increases in soil moisture after the implementation of MNREGA compared to flat pre-trends in rabi soil moisture. Results in Table 2 indicate that the annual average level of soil moisture increases by 2% after implementation of MNREGA. But the effect in the rabi season, when irrigation is most important, is substantially larger, with soil moisture over the course of the rabi season increasing by an average of 6% after MNREGA implementation.

The increase in soil moisture we document is consistent with the results in Table 3 and Figure 4 showing an increase in the area irrigated across a range of crops after the implementation of MNREGA. For each of rice, wheat, and cotton, farmers increase the share of crop area irrigated by approximately 15% after the implementation of MNREGA. Farmers increase the area irrigated in fruits and vegetables by an even larger 34%. The event studies for each crop show generally flat pre-trends leading up to MNREGA implementation. These irrigation results suggest that MNREGA eased access to reliable groundwater and farmers, who were previously constrained by access to groundwater, responded by irrigating more of their cropped area. It also offers a potential explanation for previous evidence that farmers planted riskier but higher value crops after the implementation of MNREGA (Hari and Raghunathan, 2017).[19]

[19] Increased access to reliable groundwater is certainly not the only reason farmers would shift crops after MN-

Where does this additional water for irrigation come from? The majority of irrigated land prior to the implementation of MNREGA was irrigated with water from wells. Our hypothesis indicates that farmers should have further increased their irrigated area by using water from these groundwater wells but not necessarily from other sources of irrigation. This is because, if MNREGA improved access to groundwater by facilitating recharge, it should have lowered access costs for these wells and consequently increased the area irrigated by these wells. If, by contrast, the increase in irrigated area was due to MNREGA's improvements in other irrigation infrastructure, we should observe increases in area irrigated by non-well sources.

We can test this implication of our hypothesis directly using data from ICRISAT on the area irrigated. In Table 4 we show that farmers increase the area irrigated with water from wells by roughly 17% after the implementation of MNREGA. Like with our other outcomes, the event study (Figure 5) shows no meaningful pre-trends prior to MNREGA implementation. When we examine the change in area irrigated by canals, tanks, or "other sources" we see no significant (economic or statistical) change in area irrigated from any of these sources.[20] The event study for area irrigated by canals, estimated using the method in Borusyak et al. (2024), may suggest some increase in area irrigated by water from canals (Figure 5B). However, our difference-in-difference estimates (Table 4, column 2) indicate no significant change in area irrigated by canals. The point estimate suggests a small, 3% increase with wide (-9% to 16%) confidence intervals. This is confirmed by the event studies estimated using the method in Callaway and Sant'Anna (2021) which do not suggest a meaningful increase in area irrigated by canals in the post period (Figure A6).

Collectively, our results on soil moisture, irrigated crop area, and area irrigated by source all suggest that after the implementation of MNREGA farmers increase their use of irrigation. The source of the additional water that they use for irrigation comes overwhelmingly from wells rather than the other potential sources of irrigation water. That suggests that the primary way that MNREGA projects influenced the ease of irrigation was by changing the level of groundwater during the dry season. That facilitates farmers planting more area in higher value, more water intensive crops.

5.3 Robustness checks

5.3.1 Impacts by MNREGA phase

In order to understand how impacts might vary by MNREGA phases we re-estimate our primary model comparing only two phases at a time. This helps to address concerns about non-random assignment of districts to phases if effects are consistent across phases. We report these results in

REGA. As the authors note, MNREGA relaxed credit constraints and implicitly provided insurance that may have allowed farmers to make riskier choices in their crop choices.

[20] The lack of change in area irrigated by canals or "other sources" is consistent with a world in which the availability of canal irrigation water is not due solely to the quality of the local infrastructure but also the infrastructure at distant locations where water is transported from, as well as the availability of water at those locations (e.g. Duflo and Pande (2007)). As a result, local improvements in canal infrastructure, made as part of MNREGA projects, might not be expected to yield the same benefits in terms of availability of irrigation water as improvements that would improve recharge rates.

Table A5 and find that our estimated effects are broadly consistent with the pooled results when we estimate comparing phase 1 districts with only phase 2 or only phase 3. In both cases the depth to water declines across all four seasons, although the effect in the Monsoon season is smaller when comparing phase 1 and phase 2 districts. Comparing phase 2 to only phase 3 we again see similar results to the main results and to the only phase 1 comparisons.

Broadly, the consistency in the magnitude of the results across the individual phase comparisons gives us more confidence that our results are not driven either by the particular features of districts that were included earlier or later in MNREGA. It suggests that our results are not driven by differential effects across early- or late-adopters. It also does not appear to be the case that the results are driven by large changes in any single phase or year, which could have been driven by idiosyncratic weather shocks.

5.3.2 Omitting Haryana, Punjab, and Gujarat

Haryana, Punjab, and Gujarat all implemented programs to conserve groundwater resources after the roll-out of MNREGA. While these changes are not coincident with the MNREGA roll-out, because they occur in the post period, our estimated effects of MNREGA may be biased upwards if they are picking up the impacts of these programs as well. In Table A7 we re-estimate our main specification without these three states. Our results remain broadly similar - we see declines in the depth to groundwater across all four seasons. The magnitude of our estimates without Haryana, Punjab, and Gujarat are indistinguishable from our primary results.

5.3.3 Omitting RGGVY

In 2005 the Indian government rolled out a national program ("Rajiv Gandhi Grameen Vidyutikaran Yonana" (RGGVY)) intended to electrify those villages that remained un-electrified or were "under-electrified" (see Burlig and Preonas (2016) for more detail). This program was specifically designed to provide household electrification. The transformer upgrades that occurred were intentionally designed so as not to facilitate more groundwater pumping. However, it is still possible that the program impacted groundwater pumping. To test this we re-estimate our primary specification dropping all districts that received RGGVY funding in the 10^{th} five year plan.

Table A6 shows the results of this re-estimation. We find broadly similar results, with substantial reductions in depth to groundwater during all four seasons. The impacts might be slightly smaller than in our primary specification but they are not clearly statistically different from our primary results.

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5.4 Alternative effects of MNREGA

MNREGA was primarily intended as an employment guarantee program for rural workers, who, prior to MNREGA, were predominantly agricultural laborers. In places where MNREGA was well-implemented, the places we document improvements in groundwater levels, it was effective in providing employment for these rural workers (Imbert and Papp, 2014). This raises the concern that our results are driven not by improvements in recharge due to infrastructure improvements, our interpretation of our results, but rather because MNREGA reduced the number of individuals working in agriculture and so reduced demand for water. We have two pieces of evidence that we believe suggest this shift in labor is not driving our results.

First, the majority of individuals working in agriculture in India are wage laborers who do not own or lease their own land (Saini et al., 2020). Shifting these workers out of agriculture and into MNREGA employment does not necessarily reduce demand for water as landowners who had previously employed these workers can shift to labor saving production technologies to maintain production levels (Behrer, 2023).

Second, we show increases in both area irrigated by crop and area irrigated from wells after the implementation of MNREGA. That indicates an increase in demand for groundwater in agriculture. It is hard to square an increase in groundwater driven by reductions in demand due to agricultural exit with subsequent increases in demand for water. We also show that average soil moisture during the rabi season increased after the implementation of MNREGA. This suggests that more water is being applied to fields after the implementation of MNREGA compared to pre-MNREGA. As precipitation is essentially zero during the rabi season this increase has to come from increased irrigation and our results indicate that the increase in irrigation water comes almost exclusively from increased use of groundwater. Collectively these results suggest that it is not just some farmers (i.e. those who remain after exit) increasing water use on their plots but that aggregate water use in irrigation is higher during the rabi season after MNREGA than prior to MNREGA.

It is difficult to reconcile these results - which point directly to an increase in demand for water despite potential exits from agricultural labor - with the hypothesis that higher groundwater levels are due to decreased demand for water due to exit from agriculture. Any explanation that relies on the other effects of MNREGA (employment, general economic improvements, etc) must reconcile both of these results: groundwater levels rise in areas that see strong MNREGA implementation and water use in agriculture increases, specifically water use from wells, in those areas.[21]

Such an explanation must also reconcile the timing of these effects. The majority of MNREGA projects occurred during the rabi season (Imbert and Papp, 2014) – after rabi groundwater measurements are taken, not the monsoon or kharif season. We observe increases in groundwater availability at the start of the rabi season. That implies that the increase in groundwater we document primarily occurs prior to any exit from agriculture due to MNREGA would occur. We document increased demand for irrigation water at precisely the time of year that MNREGA driven agricultural exit should have led to less demand, while we observe increased recharge during the season when MNREGA driven exit should have had the smallest effects.

[21]The alternative explanations can generally explain one of the effects we document - for example, increased economic activity might have led to increased demand for water - but not both. To continue the example, increased economic activity should have led to increased demand for water in all seasons, which does not explain the increased recharge that we observe.

6 Impact on farm revenues

By facilitating recharge that raised groundwater levels MNREGA appears to have led to an increase in the cropped area that farmers irrigated. A number of recent papers have shown that increases in access to groundwater can increase the productivity of Indian farmers (Bhattarai et al., 2021), increase farm profits (Ryan and Sudarshan, 2020), and reduce rural poverty (Sekhri, 2014). Those results pose a natural follow-on question to our main effects: how much did the improved access to groundwater due to MNREGA benefit farmers?

Answering this question is not straightforward. Because MNREGA had a variety of impacts on rural economies that plausibly effected farmer income and profits through channels other than changes in groundwater levels we cannot simply apply the identification strategy we use in our main approach to estimate the impact on farm income or profits.[22] Instead, we derive a predicted change in farmer incomes based on our estimated changes in groundwater levels and the changes in farmer production due to changes in groundwater levels that have been empirically measured in other work. Specifically, we rely on the estimated impact of a 1m change in depth to groundwater on farm productivity for rabi season plantings in Bhattarai et al. (2021).[23]

We start with our estimates of the change in the depth to groundwater at the start of the rabi season after the implementation of MNREGA. We find that, on average, depth to groundwater declines by 1.23 meters after the implementation of MNREGA in Star states relative to the average depth to groundwater in the three years prior to the implementation of MNREGA in those states. Using the estimated change in production of rabi rice and rabi wheat from Bhattarai et al. (2021) per 1 meter change in depth to groundwater, combined with the average production of these crops in Star states in the three years prior to MNREGA implementation, we estimate that higher ground water facilitated an increased production of rabi rice by 6,793 tons and rabi wheat by 3,882 tons in Star states after the implementation of MNREGA.[24]

Using market prices of rice and wheat assembled by the Centre for Economic Data & Analysis at Ashoka University we can convert these changes in production into changes in gross income for farmers.[25] We find that the increase in production of rabi rice generates an additional 75 million ₹

[22]We're not interested in the overall impact of MNREGA on these outcomes here but rather the portion of these total effects that can be attributed to the change in groundwater levels we document. This same challenge applies in the context of our main estimation but in that estimation we rely on the assumption that the only way MNREGA would have led to higher groundwater levels is via changes in infrastructure facilitating recharge. As we discuss in 5.4 there are other channels through which MNREGA might have impacted groundwater levels but they do not appear to explain the full set of our results.

[23]For the full details of these calculations see Appendix A3 . In our analysis of the impact of higher groundwater levels on production we do not consider the change in fruits and vegetables because Bhattarai et al. (2021) do not provide estimates of the productivity impacts of groundwater on these crops.

[24]These changes are relative to a counterfactual of higher groundwater levels but no other changes induced by MNREGA. The assumption of no other changes in agricultural markets due to MNREGA are clearly not satisfied and so our predicted changes in production should not be interpreted as predictions of the actual change in production after the implementation of MNREGA. Rather, they are estimates of one component of the change in farmer incomes and profits due to MNREGA. In practice the other impacts of MNREGA on farmer income and profits could have added to or subtracted from these estimated changes.

[25]We use the average of rice and wheat across all of India, taken over the years from 2009 to 2013, following MNREGA implementation. Data available here: `https://agmarknet.ceda.ashoka.edu.in/`

in gross income for farmers annually and the increased wheat production generates an additional 49 million ₹ in gross income.

Using data on production costs from Bhattarai et al. (2021) and CACP (2011) we can also estimate the change in farm profits that comes from this increase in production. Accounting for production costs suggests that the increase in production results in an additional 9 million ₹ from rabi rice production and 12 million ₹ from rabi wheat production. These estimated changes in profits are similar to the benchmark that a back of the envelop calculation using data from Ryan and Sudarshan (2020) would suggest. They find that an increase in depth to groundwater in Rajasthan reduces farm profits by 155 ₹/HA per meter. Using this estimate and the total area planted on average in rabi rice and rabi wheat in Star states prior to MNREGA we estimate an increase in farm profits of approximately 17 million ₹ annually based on our actual change in depth to groundwater.

All of these estimates of the change in gross farm income and farm profits are a rough approximation of the benefits of the reduction in depth to groundwater. These calculations make significant assumptions about the symmetry of effects of reducing vs. increasing depth to groundwater and use state or nationwide averages for production, profits, and costs. However, our estimates provide a ballpark figure for the benefits that farmers realized from easier access to groundwater after the implementation of MNREGA.

7 Conclusion

Access to reliable sources of groundwater for irrigation remains a critical challenge for Indian farmers. Ensuring long-term sustainability of groundwater withdrawals will likely require policies that encourage conservation (Ryan and Sudarshan, 2020). However, in areas with aquifers that have high surface level connectivity, the construction of surface level infrastructure that encourages recharge may provide a short-term solution to alleviate pressure on groundwater levels.

Our results suggest that surface level water conservation infrastructure constructed as part of the MNREGA program led to meaningful reductions in depth to groundwater in the states that implemented the largest number of these projects. This reduction likely occurred as the construction of new soft-bottomed water storage, flood management, and irrigation infrastructure allowed greater recharge of groundwater by pooling surface water after the completion of these MNREGA projects. This is possible because the high degree of connectivity between surface water and groundwater in much of India.

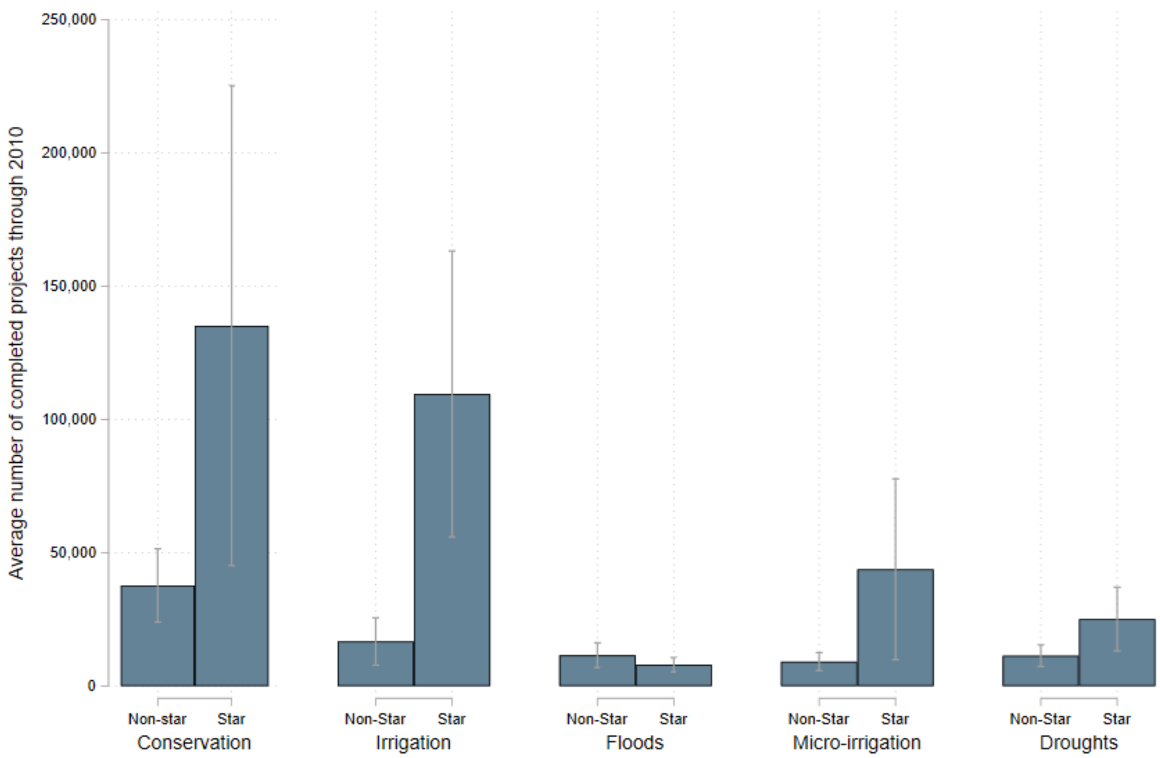
The reduction in the depth to groundwater we document likely provided farmers with more reliable and less expensive access to groundwater for irrigation, especially during the rabi season. This more reliable access to groundwater likely relaxed constraints on farmer behavior with respect to irrigation and planting choices. We observe that soil moisture, an aggregate measure of irrigation, increases noticeably after the implementation of MNREGA both in the annual average and specifically during the rabi season. We also observe farmers irrigate more area in high value, water intensive crops after the implementation of MNREGA. The water that they use for this irrigation comes from wells, as opposed to canals, tanks, or other irrigation infrastructure that might have been improved by MNREGA.

The reductions in depth to groundwater that we observe also provide some evidence that MNREGA was able to meet, at least partially, its secondary goals of providing productivity enhancing infrastructure in rural areas. It appears that water infrastructure constructed with MNREGA funds may have, *ceritus paribus*, increased the income and profits of some farmers. The cost-effectiveness of providing infrastructure in this way remains unclear and is an area for future research.

8 Tables & Figures

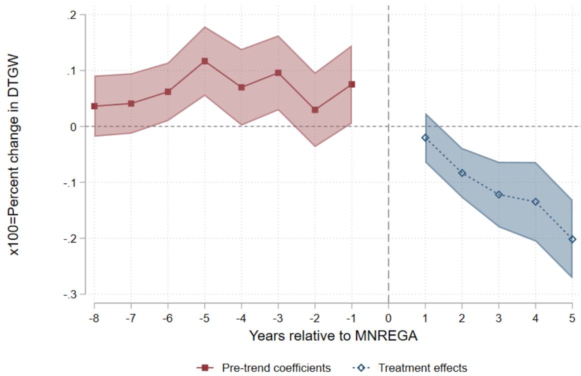
8.1 Figures

Figure 1: Average completed MNREGA projects by Star status

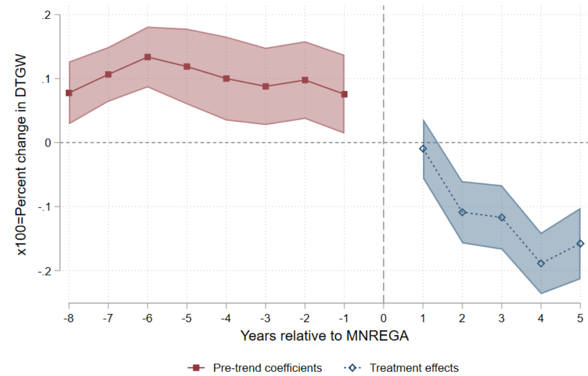


Notes: We calculate the average number of MNREGA projects in each water related category that have been completed through the end of 2010 in Star and non-Star states. Confidence intervals around the mean are shown in grey bars.

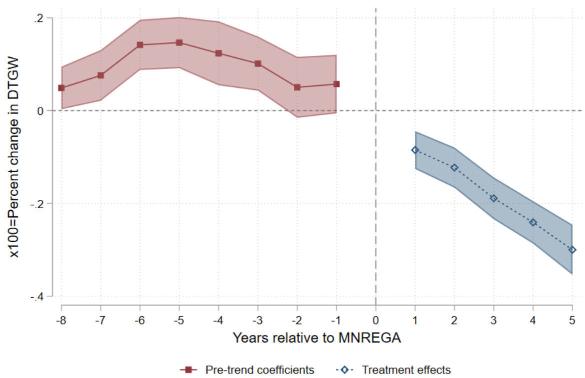
Figure 2: Seasonal water depth event studies



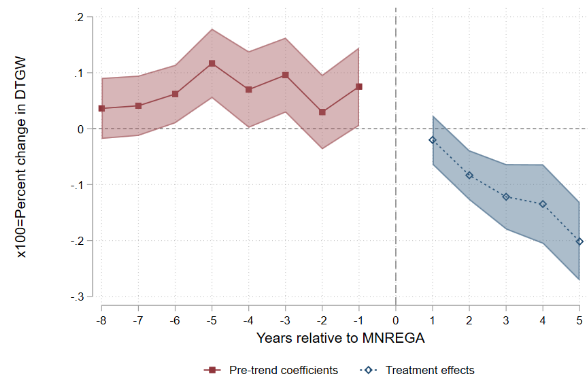
Monsoon well depths



Kharif well depths



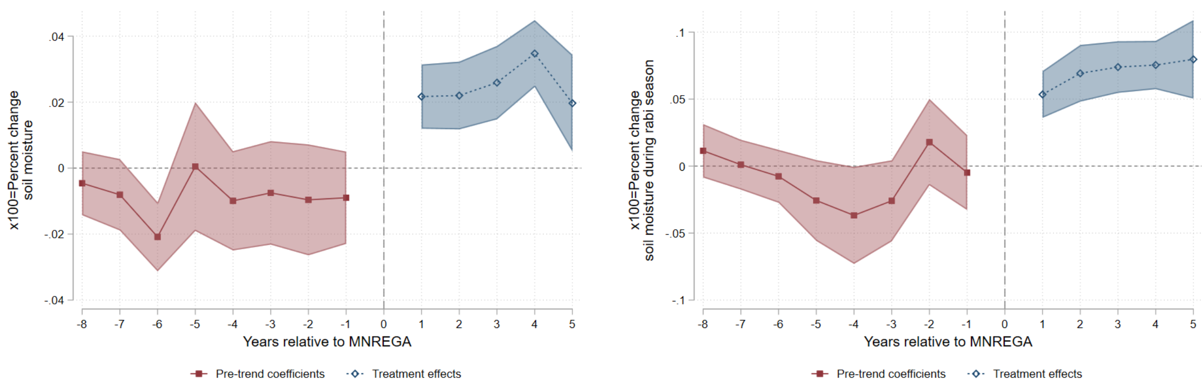
Rabi well depths



Pre-monsoon well depths

Notes: Each figure reports the coefficients on each year in event time for the well depths in the seasons indicated in the titles. We estimate each event study using the Stata packages `did_imputation` and `event_study` that implement the approaches described in Borusyak et al. (2024). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state by year quadratic trend.

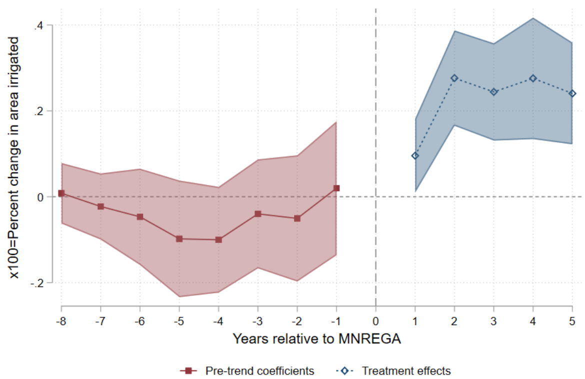
FIGURE 3: Soil moisture pre- and post-MNREGA



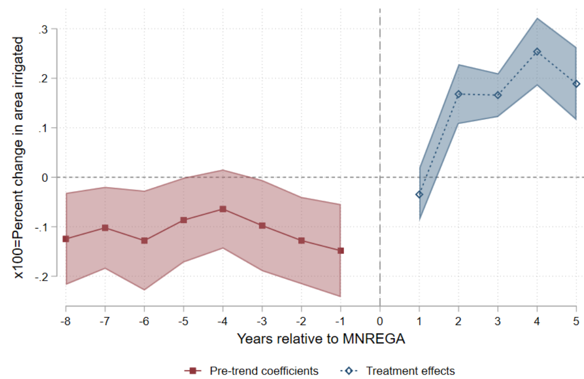
Annual Rabi

NOTES: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for the soil moisture during the seasons indicated in the titles. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Borusyak et al. (2024). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

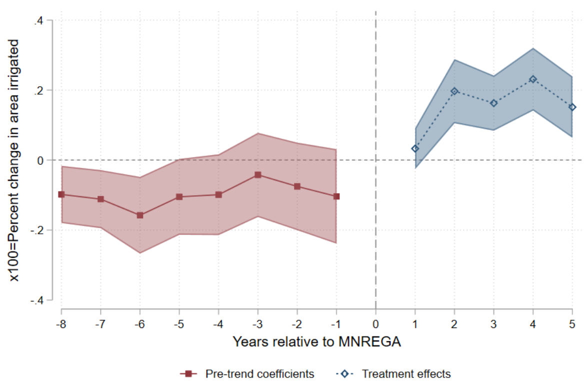
FIGURE 4: Area irrigated by crop



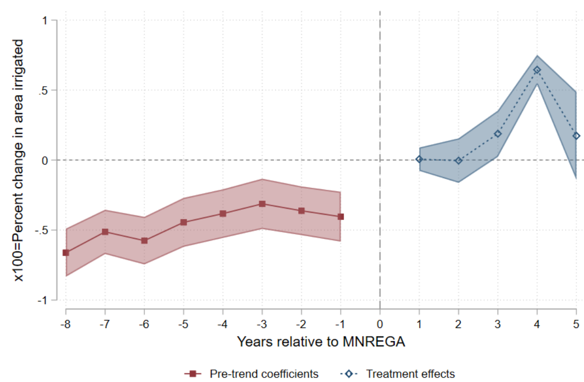
Rice



Wheat



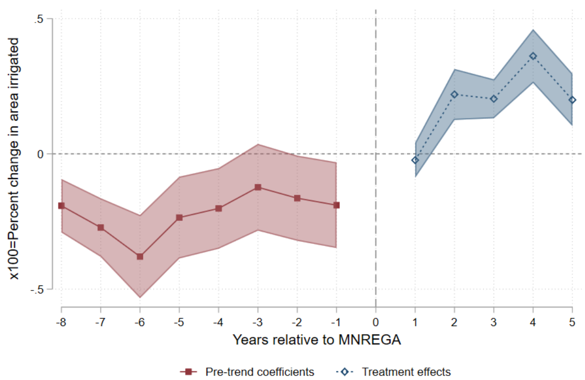
Cotton



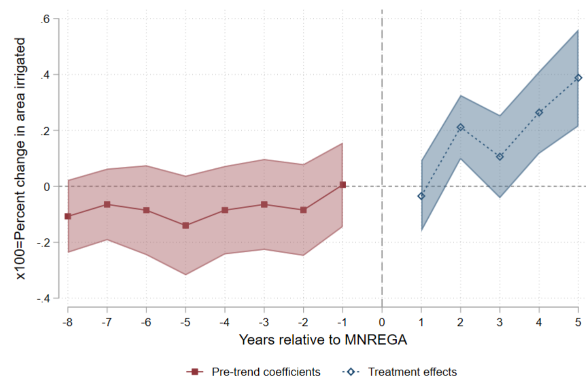
Fruits & Vegetables

NOTES: Each figure reports the coefficients on each year in event time for the area irrigated of the crop indicated in the titles. We estimate each event study using the Stata packages `did_imputation` and `event_study` that implement the approaches described in Borusyak et al. (2024). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state by year quadratic trend.

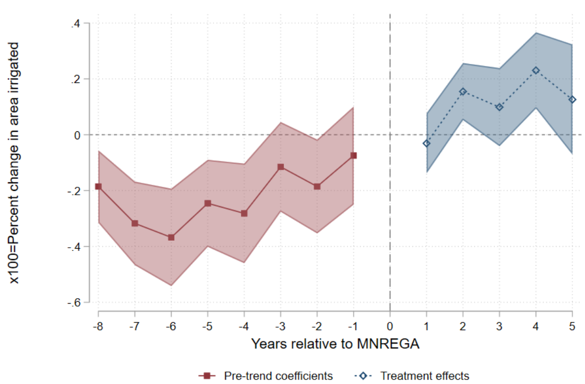
Figure 5: Area irrigated by source



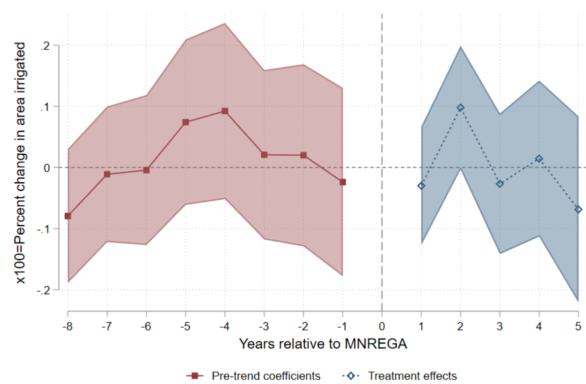
From wells



From canals



From tanks



From other sources

Notes: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for area irrigated from each source. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Borusyak et al. (2024). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

8.2 Tables

Table 1: Impact of MNREGA on seasonal depth to groundwater

	Monsoon	Kharif	Rabi	Pre-monsoon
Post-MNREGA	-0.07	-0.08	-0.15	-0.11
	(0.03)	(0.02)	(0.02)	(0.02)
95% CI	[-0.13,-0.01]	[-0.13,-0.04]	[-0.20,-0.10]	[-0.15,-0.07]
N	6355	6939	6932	6852
Pre-MNREGA mean (m)	6.10	6.16	6.81	8.21
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. 100× the coefficient is the percent change in the depth to water after the implementation of MNREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

Table 2: Impact of MNREGA on soil moisture

	Full year	January-April
Post-MNREGA	0.02	0.06
	(0.01)	(0.01)
95% CI	[0.01,0.03]	[0.04,0.09]
N	6960	6944
Pre-MNREGA mean (m^3/m^3)	2.26	1.81
Fixed Effects:		
District	Yes	Yes
Year × month	Yes	Yes

Notes: Our outcome is the IHS transformation of soil moisture in the period specified in the column heading. Soil moisture is measured as cubic meters of water in a cubic meter of soil. We measure the district average level of soil moisture over the full year and the Rabi season for each year in our sample. All regressions include controls for temperature, a quadratic control for precipitation and a quadratic state × year trend. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

Table 3: Impact of MNREGA on share of crop area irrigated

	Rice	Wheat	Cotton	Fruits & Vegetables
Post-MNREGA	0.16	0.16	0.15	0.34
	(0.04)	(0.04)	(0.05)	(0.08)
95% CI	[0.08,0.24]	[0.09,0.24]	[0.06,0.23]	[0.19,0.49]
N	6021	6021	6021	6021
Pre-MNREGA mean (000ha)	49.93	54.72	6.71	8.30
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the area in each crop in each district-year that is irrigated. 100× the coefficient is approximately the percent point change in the area irrigated after the implementation of MNREGA. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

Table 4: Impact of MNREGA on area irrigated by source

	Area irrigated by:			
	Wells	Canals	Tanks	Other
Post-MNREGA	0.17	0.04	-0.02	-0.04
	(0.05)	(0.06)	(0.05)	(0.05)
95% CI	[0.07,0.27]	[-0.09,0.16]	[-0.12,0.09]	[-0.14,0.06]
N	6021	6021	6021	6021
Pre-MNREGA mean (000ha)	76.45	35.63	7.24	5.38
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the area irrigated by each irrigation source. 100× the coefficient is the approximate percent change in the area irrigated after the implementation of MNREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

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Appendix – For Online Publication

A1 Effects based on full, staggered MNREGA roll-out

Our primary specification takes advantage of the heterogeneity in implementation to define a "Never Treated" control group of districts that received MNREGA but were in states that did not have high quality implementation (Imbert and Papp, 2014; García, 2022). This approach contrasts with much of the existing literature on the impacts of MNREGA that uses only the staggered roll-out of the program (e.g. Shah and Steinberg (2015); Behrer (2023)) for identification. Our approach relies on two assumptions: (1) that trends in the depth to groundwater in each of the four seasons for which we have measurements were trending similarly prior to MNREGA implementation in both "star" and "non-Star" states and (2) that districts located in non-Star states did not receive any benefit (or harm) from (non-) implementation of MNREGA.

While the most likely violation of the second assumption - that non-Star districts experience some positive effect on groundwater levels, either due to within sub-basin spillovers (see Appendix A2) or because MNREGA projects in non-Star states also led to small amounts of recharge - would bias our results towards zero, we can implement a more standard (in the MNREGA literature) estimation strategy that does not require this assumption and relies only on the staggered roll-out of MNREGA across the country.

This imposes only a variant of the first assumption, that trends in depth to groundwater were the same in each phase in the years preceding implementation of MNREGA. It has the disadvantage of lacking a true "Never Treated" group and so is subject to the concerns that the new DiD literature has identified (Callaway and Sant'Anna, 2019; Goodman-Bacon, 2018; Borusyak et al., 2024).[26]

Nonetheless, as a robustness check we estimate our main results using this more standard approach. We estimate variations of the following base specification:

$$\text{Depth}_{iy} = \beta \mathbb{1}\left[\text{NREGA}_{iy}\right] + \psi \text{Precip}_{iy} + \omega \text{Precip}^2_{iy} + \theta \text{Temp}_{iy} + \alpha_i + \chi_y + \eta_s + \epsilon_{iy} \tag{2}$$

where Depth_{iyq} is the inverse hyperbolic sine transformation of the average depth to groundwater in district i, year y, and season q. Larger numbers indicate that wells must be deeper, and therefore more expensive, to reach groundwater. Depth measurements are taken during the monsoon, at the end of the kharif season, during the rabi season, and prior to the start of the monsoon. We include a quadratic in the total precipitation the district receives in a year and control for the average temperature in the district during the year. We also include district (α) and year (χ) fixed effects and a quadratic state $\times$ year (η) trend. We cluster standard errors at the district level (Abadie et al., 2017).

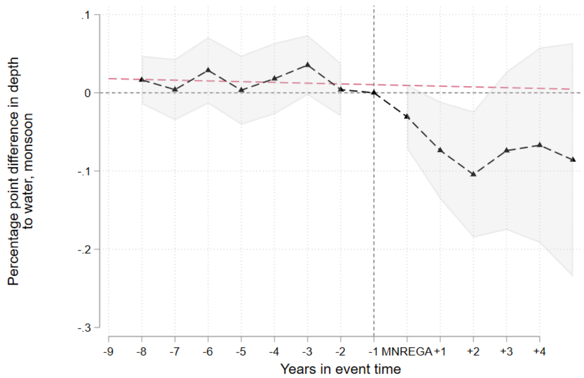
We present the event studies of the results for our primary outcome - depth to groundwater in each season - using this approach below. We also present tabular results from the difference-in-differences estimates for each of our other main outcomes. In the event studies we follow Dobkin et al. (2018) and Rambachan and Roth (2023) and plot, in dashed red-lines, the trendlines of the pre-period event coefficients into the post-period. This allows for comparison of the post-period effects against both the null of zero effect and the null of continuation of any pre-period trends. However, broadly, across the outcomes we examine here we do not observe evidence of pre-trends.

[26] It is worth noting that the nature of MNREGA treatment - tightly clustered in the center of a relatively long panel - suggest that many of the concerns raised in this literature are less of an issue in this context.

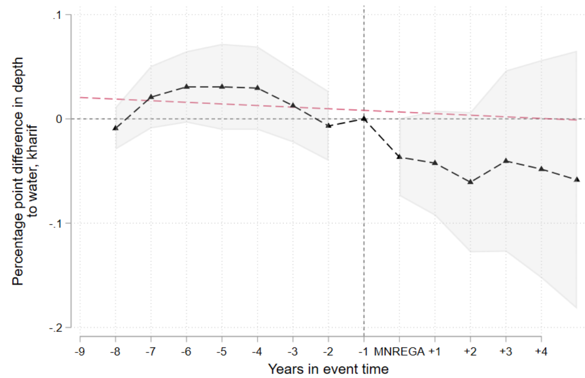
Our results using only the staggered roll-out of MNREGA are broadly similar to those in our preferred approach (Figure A1). We find that depth to groundwater declines after implementation of MNREGA in both the monsoon and kharif seasons. In the full sample these effects are somewhat smaller than in our preferred estimates and are estimated with more uncertainty. This is consistent with the effects being driven primarily by impacts in a limited number of states that implemented the program more effectively, with effects close to zero in other states. This is likely due to increases in the depth to groundwater in non-Star states due to continued irrigation demand and a lack of recharge. This increase in depth to groundwater in these states offsets the positive effect of MNREGA in Star states and yields a near zero effect across all districts.

Our tabular results confirm what the event studies show, suggesting declines in depth to groundwater in each season, with reductions in the monsoon and kharif seasons. Our effects in the rabi season and the pre-monsoon season are both close to zero. This, again, is consistent with reductions in depth to groundwater in these seasons in the Star states being offset by continued increases in depth to groundwater in the non-Star states.

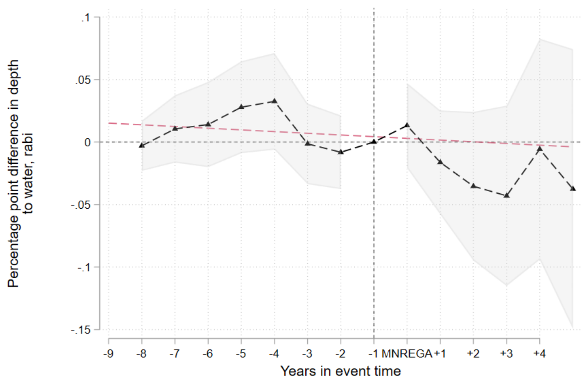
Figure A1: Seasonal water depth event studies



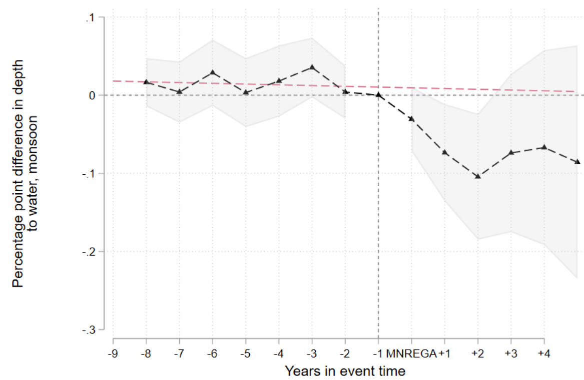
Monsoon well depths



Kharif well depths



Rabi well depths



Pre-monsoon well depths

Notes: Each figure reports the coefficients on each year in event time for the well depths in the seasons indicated in the titles. We estimate each event study using all districts in India and relying only on the staggered roll-out of MNREGA for identification. Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state by year quadratic trend. The dashed red line indicates the linear best fit line of the pre-period event coefficients, extended to the post-period in the spirit of (Dobkin et al., 2018; Rambachan and Roth, 2023).

Table A1: Impact of NREGA on seasonal depth to groundwater

	Monsoon	Kharif	Rabi	Pre-monsoon
Post-NREGA	-0.043**	-0.033**	0.010	-0.004
	(0.019)	(0.016)	(0.014)	(0.012)
N	6,989	7,568	7,581	7,489
Outcome mean, Pre-NREGA (m)	6.65	6.73	7.42	8.80
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. 100× the coefficient is the percent change in the depth to water after the implementation of NREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. Errors are clustered at the district level.

A2 Estimation at district vs. sub-basin level

Assessment at the district level means there may be cases in which a sub-basin is below both a treated and untreated district. For our analysis, we assign the portion of the sub-basin (i.e. the wells that measure depth in a particular part of a sub-basin) that falls within a district to that district. Therefore, if a sub-basin falls below two districts, one treated and one not treated, only the depth measured in the portion that falls within the treated district is considered to be treated. Where sub-districts have low horizontal connectivity, such that withdrawals in one district would not be quickly reflected in another, this is not a problem.[27] However, if a sub-district is highly horizontally connected and lies under both a treated district and a non-treated district, the depth to water in the area under the non-treated district will likely to be affected by changes in the treated district.

The impact of treatment raising groundwater under non-treated districts because of sub-basin connectivity may lead to underestimates of the treatment effect of MNREGA. In this case our results should be viewed as a lower-bound on the effect of MNREGA projects on improving groundwater access.

To see why, again consider highly horizontally connected sub-basins with at least two districts that overlap the sub-basin aquifer. One district (i) is treated at time t and one district (j) is treated at time *t+1* (or is Never Treated - the logic in what follows is true if one replaces early treated with Star treated and late treated with non-Star). That means district j is in the control group when assessing the treatment effect in district i. In the first treated district the treatment effect will be measured as

$$\underbrace{\left[DTGW_{i,t} - DTGW_{i,t-1}\right]}_{\text{Difference 1}} - \underbrace{\left[DTGW_{j,t} - DTGW_{j,t-1}\right]}_{\text{Difference 2}}$$

If MNREGA results in lower DTGW this will be reflected by $DTGW_{i,t} - DTGW_{i,t-1}$ being negative. However, because the aquifer has high horizontal connectivity the DTGW across the entire aquifer - even under untreated districts - at time t will be lower. That implies that $\left[DTGW_{j,t} - DTGW_{j,t-1}\right]$

[27]By horizontal connection we mean the level of flow in the aquifer from one part of the aquifer to another. We use horizontal to distinguish this type of connectivity from the surface connectivity (vertical connectivity) that we primarily study.

will also be negative despite district j not receiving treatment and so will result in the total difference $\left[DTGW_{i,t}-DTGW_{i,t-1}\right]-\left[DTGW_{j,t}-DTGW_{j,t-1}\right]$ being an underestimate of the true treatment effect in district i.

If treatment effects are growing over-time then we have the familiar problem of staggered DiD designs where our estimates of the treatment effect in district j will also be an underestimate because district i will be in the control group for district j at time $t+1$. The estimate of the treatment effect in district j is

$$\underbrace{\left[DTGW_{j,t+1}-DTGW_{j,t}\right]}_{\text{Difference 1}}-\underbrace{\left[DTGW_{i,t+1}-DTGW_{i,t}\right]}_{\text{Difference 2}}$$

Non-stable treatment effects over time mean that $\left[DTGW_{i,t+1}-DTGW_{i,t}\right]$ is not a valid counterfactual for $\left[DTGW_{j,t+1}-DTGW_{j,t}\right]$ in the absence of treatment because $DTGW_{i,t+1}$ is a consequence, in part, of lagged treatment effects from treatment in time t. This is the standard problem with non-stable treatment effects in staggered DiD (e.g. Goodman-Bacon (2018)). This problem is made more complex in our setting because the growing treatment effect in i will result in a direct change in DTGW in district j. That is, $DTGW_{j,t+1}$ will also be a consequence, in part, of lagged treatment effects from treatment in time t in district i because of the aquifer connectivity.

While we cannot fully calculate the magnitude of the bias introduced by non-stable treatment effects and aquifer connectivity, we can place some bounds on it. In the extreme case, where connectivity is high such that spill-overs via connectivity occur quickly the additional lagged treatment effects in $DTGW_{i,t+1}$ and $DTGW_{j,t+1}$ will be equal and so will net out of the DiD estimates. In this case the bias is zero. The standard staggered DiD bias disappears because the lagged treatment effect appears in both terms of the difference equation because of the aquifer connectivity. In the case where connectivity is lower and so there is a delay in spillover effect operating via the connectivity channel our estimates will be an underestimate of the true effect because the portion of the lagged treatment effect that appears in the second term of the difference equation (in $DTGW_{i,t+1}$) will be larger than what appears in the first term (in $DTGW_{j,t+1}$). This will result in a smaller overall difference in later treated units. We then assess MNREGA's treatment effect in the later treated district j as $DTGW_{j,t+1}-DTGW_{j,t}$.[28] For non-horizontally connected aquifers there is no bias either via the connectivity channel because early treatment in one district will not change groundwater levels under other districts if they are not horizontally connected.

A3 Calculation of farm income and profit impacts

To calculate the gross income change and change in profits as a result of the decrease in depth to groundwater caused by MNREGA we take the following steps. First we assemble data on seasonal agricultural production from ICRISAT.[29] This data reports the area planted in and total production of rabi rice and rabi wheat by district and year during our sample period. We then collect estimates of production costs for paddy and rabi wheat from the 2011 agricultural census and CACP (2011).[30]

[28]This assumes growing treatment effects over-time. This assumption is consistent with both our event studies, that indicate effects grow over time, and the pattern of MNREGA implementation. The total employment, money spent on projects, and total number of projects implemented grew over time from implementation until at least 2013, after the end of our study period.

[29]Data available here: http://data.icrisat.org/dld/src/additional.html

[30]The 2011 agricultural census reports production costs of paddy in 2008-09. We inflate these to 2011 using the average Indian CPI. Using the uninflated 2008-2009 numbers yields similar, though slightly larger, profit results.

We collect market prices of paddy and wheat from the Centre for Economic Data & Analysis at Ashoka University (CEDA). This data is built with raw data from the Ministry of Agriculture and Farmers Welfare and is based on quantity arrivals and producer prices at agricultural markets in India. We collect nationwide averages of the producer prices from January 2009 to January 2013. These prices are based on averaging several million price reports across thousands of markets.[31]

Our calculation then proceeds in the following steps. We estimate the change in depth to groundwater at the start of the rabi season in Star states as

$$\Delta DTGW_{Starstates} = \widehat{DTGW_{Starstates}} \times \beta$$

where hats indicate the average across all Star states in the years from 2003 until treatment occurs in a specific district and β is the estimated β from Equation 1.

This provides us an estimate of the change in depth to groundwater due to MNREGA in meters. We estimate the change in production in rabi rice and wheat using this estimated change combined with the productivity impacts estimated in Bhattarai et al. (2021). Bhattarai et al. (2021) estimate the change in production of rabi season crops based on a 1 meter change in depth to groundwater at the start of the season. We apply their estimates with the following equation

$$\Delta Production_{Starstates,crop} = \Delta DTGW_{Starstates} \times \widehat{Production_{Starstates,crop}} \times \delta_{Bhattarai,crop}$$

We estimate the change in gross income as

$$\Delta Income_{Starstates,crop} = \Delta Production_{Starstates,crop} \times Price_{crop}$$

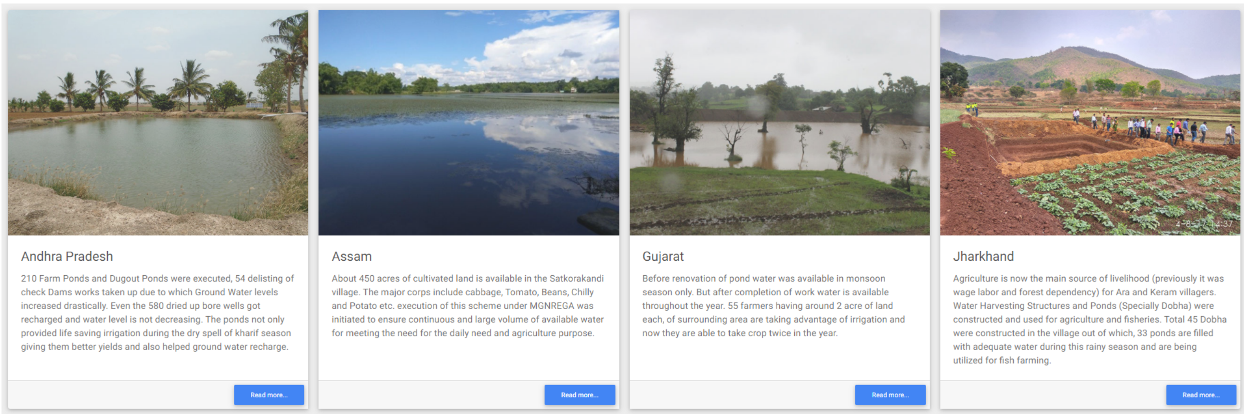
where price comes from the CEDA market data. To calculate the change in profits we take the same approach but use the difference between the price and the costs of production as the final term.

To calculate the profits using the estimate from Ryan and Sudarshan (2020) we calculate the sum of the average areas in production in rabi rice and rabi wheat across all Star states in the years from 2003 until treatment and multiply that sum by $\Delta DTGW_{Starstates}$ and the 155 ₹/HA estimate from Ryan and Sudarshan (2020).

[31] For more details see: `https://agmarknet.ceda.ashoka.edu.in/README.html`

A4 Additional Figures

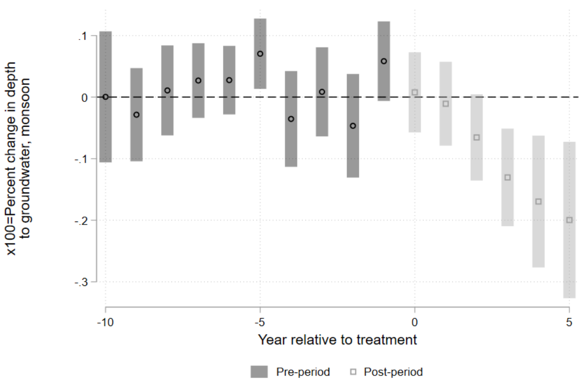
FIGURE A2: Example MNREGA projects



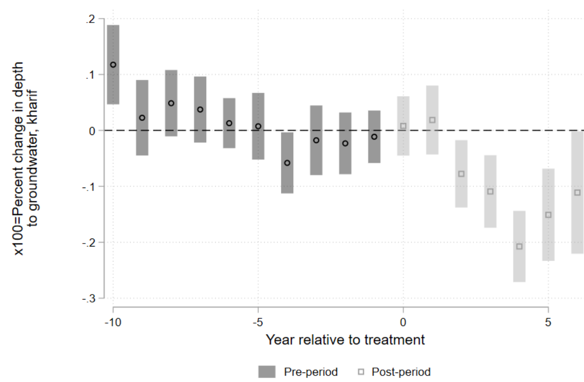
NOTES: Images are examples of projects completed using MNREGA funding presented on the MNREGA tracking website.

Figures A3-A6 correspond to Figures 2-5 in the main manuscript but are estimated using the approach described in Callaway and Sant'Anna (2021) (and their provided `csdid` Stata package), rather than the approach in Borusyak et al. (2024).

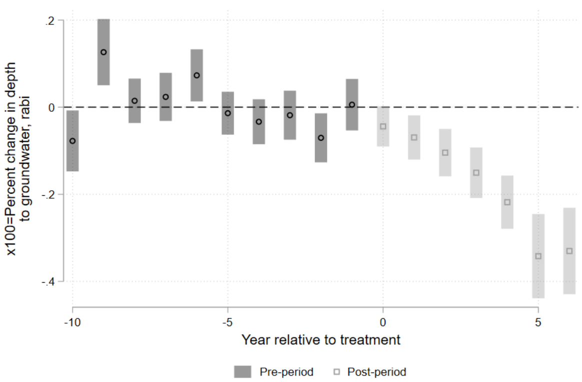
Figure A3: Seasonal water depth event studies



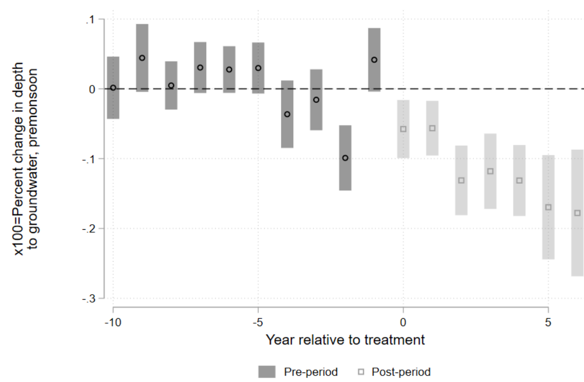
Monsoon well depths



Kharif well depths



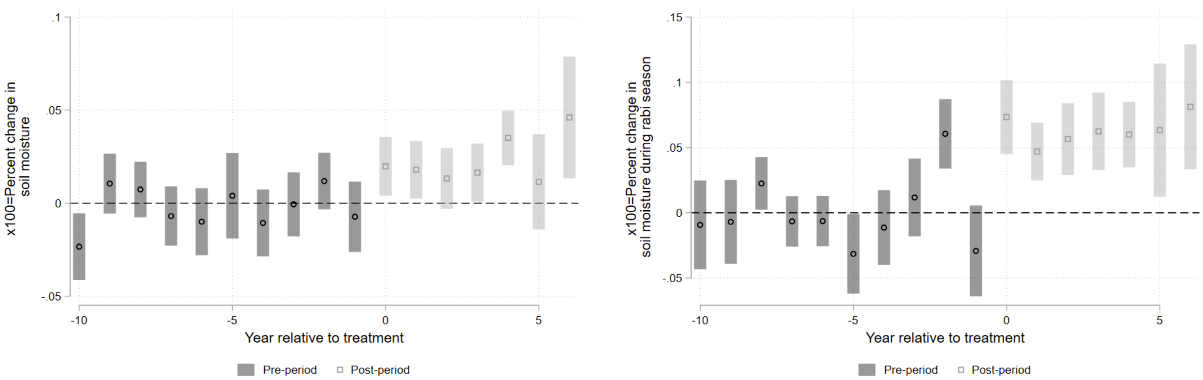
Rabi well depths



Pre-monsoon well depths

Notes: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for the well depths in the seasons indicated in the titles. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Callaway and Sant'Anna (2021). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

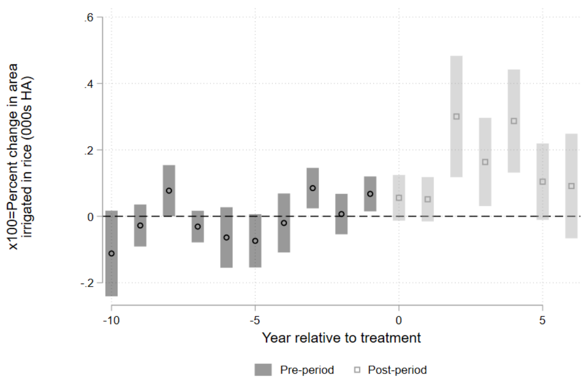
Figure A4: Soil moisture pre- and post-MNREGA



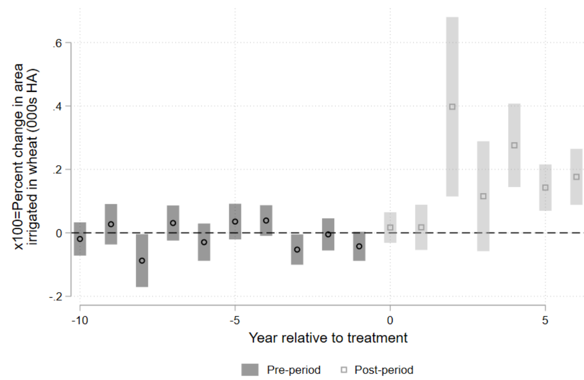
Annual Rabi

Notes: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for the soil moisture during the seasons indicated in the titles. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Callaway and Sant'Anna (2021). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

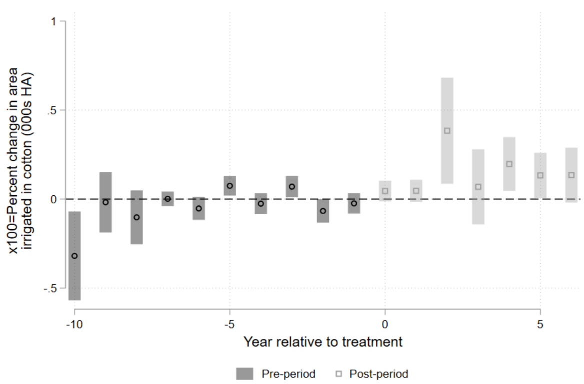
Figure A5: Area irrigated by crop



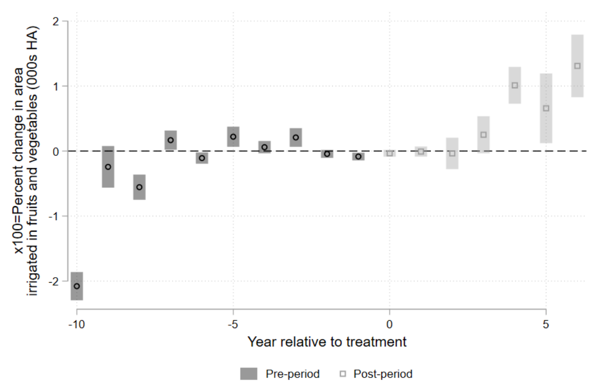
Rice



Wheat



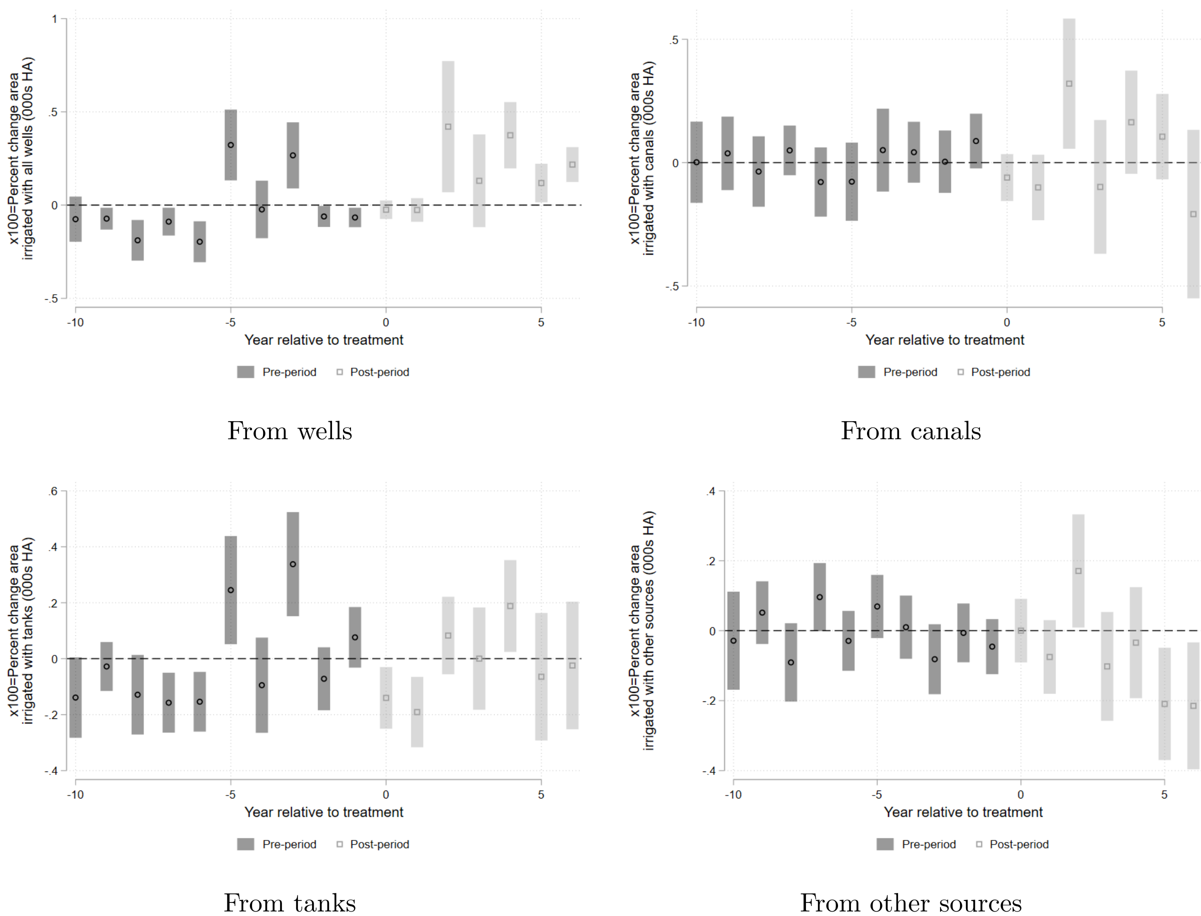
Cotton



Fruits & Vegetables

Notes: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for the area irrigated in that crop. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Callaway and Sant'Anna (2021). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

FIGURE A6: Area irrigated by source



NOTES: Each figure reports the coefficients of the difference between treated and non-treated districts in each year in event time for area irrigated from each source. Treatment is defined as being located in a Star state and turns on after implementation of MNREGA in that individual district. Our estimates are based on the approach described in Callaway and Sant'Anna (2021). Each event study is estimated with temperature and precipitation controls as well as district and year fixed effects and a state specific quadratic trend.

A5 Additional Tables

TABLE A2: Difference in water-related projects between Star and Non-star states

	Conservation	Irrigation	Drought	Flood	Micro-irrigation
% Difference (Star-Non-star)	139.52	293.86	53.29	-72.21	143.39
T-stat of difference	28.71	52.84	18.26	30.68	22.02

NOTES: Each column reports the difference in the mean number of projects completed through 2010. Types of projects are identified in the column heading. Differences are calculated as Star - Non-star and shown in the first row as a percentage of the mean in Non-star states. The second row is the t-stat of that difference in means.

Table A3: Pre-program (2006-07) differences in number of groundwater irrigation structures

	(1) Phase I Mean [sd]	(2) Phase II Mean [sd]	(3) Phase III Mean [sd]	(4) (II) - (I) Coeff (se) [p]	(5) (III) - (I) Coeff (se) [p]	(6) (III) - (II) Coeff (se) [p]
Dug wells	19592.42	10696.59	20563.30	-4157.98	-2207.92	2371.36
	[34634.58]	[20071.55]	[33617.70]	(2694.61)	(3147.69)	(2074.22)
				[0.12]	[0.48]	[0.27]
Shallow tube wells	16423.67	22546.58	17282.76	1802.79	-688.42	-2367.21
	[28974.94]	[30250.50]	[25152.10]	(2649.41)	(2146.73)	(2035.23)
				[0.50]	[0.75]	[0.26]
Deep tube wells	2133.98	2120.62	3724.52	220.13	585.84	193.33
	[7089.68]	[4916.10]	[10520.40]	(601.83)	(621.09)	(647.44)
				[0.71]	[0.35]	[0.77]

Notes: Table compares the district level number of dug wells, shallow tube wells and deep tube wells prior to the start of NREGA. The data are from the Fourth Minor Irrigation Census conducted in 2006-07. TUbe wells are classified in the Census as if they have a depth less than 70 meters, while tube wells are greater than 70 meters in depth. Columns (1) - (3) show the phase-wise means and standard deviations. Columns (4) - (6) show the difference means (after absorbing state fixed effects) along with the associated standard errors and p-values for the difference. Errors are clustered at the district level.

Table A4: Impact of NREGA projects on seasonal depth to groundwater

	Monsoon	Kharif	Rabi	Pre-monsoon
(A) Conservation				
	-0.046***	-0.066***	-0.040***	-0.049***
	(0.010)	(0.010)	(0.012)	(0.010)
N	6,489	6,591	6,602	6,584
(B) Irrigation				
	-0.054***	-0.073***	-0.050***	-0.042***
	(0.014)	(0.012)	(0.011)	(0.009)
N	6,489	6,591	6,602	6,584
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. The coefficients indicate the approximate percent change in the depth to water after the implementation of MNREGA for every 100,000 projects completed of the types listed in the leftmost column. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state $\times$ year trend. Errors are clustered at the district level.

Table A5: Impact of MNREGA on seasonal depth to groundwater by MNREGA phase

	Monsoon	Kharif	Rabi	Pre-monsoon
(A) MNREGA Phase I vs. Phase II				
Post-MNREGA	-0.02	-0.06	-0.23	-0.15
	(0.05)	(0.03)	(0.03)	(0.03)
95% CI	[-0.11,0.07]	[-0.13,0.00]	[-0.29,-0.16]	[-0.21,-0.08]
N	3326	3680	3681	3629
(A) MNREGA Phase I vs. Phase III				
Post-MNREGA	-0.09	-0.08	-0.15	-0.12
	(0.04)	(0.03)	(0.03)	(0.02)
95% CI	[-0.16,-0.03]	[-0.14,-0.03]	[-0.20,-0.10]	[-0.17,-0.08]
N	5069	5516	5517	5487
(A) MNREGA Phase II vs. Phase III				
Post-MNREGA	-0.08	-0.08	-0.08	-0.07
	(0.03)	(0.03)	(0.03)	(0.02)
95% CI	[-0.14,-0.02]	[-0.13,-0.02]	[-0.13,-0.02]	[-0.12,-0.02]
N	4313	4682	4666	4588
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. 100× the coefficient is the percent change in the depth to water after the implementation of MNREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

Table A6: Impact of MNREGA on seasonal depth to groundwater without RGGVY phase 1

	Monsoon	Kharif	Rabi	Pre-monsoon
Post-MNREGA	-0.08	-0.10	-0.11	-0.08
	(0.04)	(0.03)	(0.03)	(0.03)
95% CI	[-0.15,-0.01]	[-0.16,-0.04]	[-0.17,-0.06]	[-0.13,-0.03]
N	3831	4175	4228	4111
Pre-MNREGA mean (m)	6.51	6.74	7.33	8.78
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. 100× the coefficient is the percent change in the depth to water after the implementation of MNREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. We drop districts in phase 1 of the RGGVY program. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.

Table A7: Impact of MNREGA on seasonal depth to groundwater without Punjab, Gujarat, and Haryana

	Monsoon	Kharif	Rabi	Pre-monsoon
Post-MNREGA	-0.06	-0.08	-0.15	-0.11
	(0.03)	(0.02)	(0.02)	(0.02)
95% CI	[-0.12,0.00]	[-0.12,-0.03]	[-0.20,-0.10]	[-0.15,-0.07]
N	6160	6684	6679	6599
Pre-MNREGA mean (m)	6.05	6.12	6.77	8.17
Fixed Effects:				
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: Our outcome is the IHS transformation of the depth to water in each season specified in the column heading. 100× the coefficient is the percent change in the depth to water after the implementation of MNREGA. All regressions include controls for monthly temperature, a quadratic control for monthly precipitation and a quadratic state × year trend. We drop districts in Punjab and Haryana after 2009. We also drop districts in Gujarat after 2006. Errors are clustered at the district level. Our estimates are based on the approach described in Callaway and Sant'Anna (2021) and implemented using their Stata package `csdid`.