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ORIGINAL ARTICLE

Public works programmes and agricultural risk: Evidence from India

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Abstract

The agricultural sectors in many low- and middle-income countries remain highly vulnerable to weather risk, a vulnerability that will only intensify under climate change. The globally trending public works programmes have the potential to impact weather-related agricultural risk. I explore the impact of India's National Rural Employment Guarantee Act (NREGA) on weather-related agricultural risk. My empirical strategy explores the staggered roll-out of NREGA and random weather fluctuations. Using a nationwide panel of data, I find that NREGA makes crop yields more sensitive to low rainfall shocks. I posit that these results are consistent with a labour market channel, by which NREGA increases nonfarm labour supply in low rainfall years, and an income channel, by which NREGA leads to riskier agricultural practices. These results highlight the importance of understanding how social protection programmes shape agricultural risk.

KEYWORDS

agriculture, India, production risk, public works, workfare

JEL CLASSIFICATION

J43, O12, O13, Q56

1 | INTRODUCTION

Despite growth and industrialisation, many low- and middle-income countries (LMICs) remain heavily reliant on agriculture for both GDP and employment (Steinbach, 2019). Furthermore, the agricultural sectors in many LMICs continue to be highly exposed to weather risk, a risk exposure that will likely intensify as climate change accelerates (World Bank, 2015). Uninsured risk substantially reduces welfare in LMICs (Dercon, 2002) and has been shown to inhibit the use of intermediary agricultural inputs (Donovan, 2021) and to reduce agricultural productivity (Cole et al., 2017; Karlan et al., 2014). Thus, reducing farmers' weather risk exposure is a top policy priority (Ward et al., 2020). Weather-related agricultural risk can be reduced via many channels, such as diversifying crop portfolios (Auffhammer & Carleton, 2018), purchasing formal insurance (Cole & Xiong, 2017; Ward et al., 2020), investing in irrigation (Zaveri & Lobell, 2019), adopting agricultural technologies such as drought- or flood-tolerant crop varieties (Emerick et al., 2016) or shifting agricultural labour to other sectors of the economy (Colmer, 2021; Liu et al., 2022).

Social protection programmes, including public works programmes, offer another potentially important channel for reducing weather-related agricultural risk. Public works programmes generate employment for poor households while simultaneously creating labour-intensive public good infrastructure; thus, these programmes have the potential to reduce weather-related agricultural risk by providing a nonagricultural income source and by enhancing agriculture-related public goods. Public works programmes have been gaining popularity in the global South—being recently implemented in countries including Argentina, Ethiopia, India, Rwanda and South Africa—and researchers have demonstrated numerous economic and social benefits of these programmes (Gehrke & Hartwig, 2018). Despite the growing importance of public works programmes, few papers have studied their potential role in shaping weather-related agricultural risk.

In this paper, I analyse the impact of social protection programmes on weather-related agricultural risk. In particular, I study the effects of a large-scale workfare programme in India, National Rural Employment Guarantee Act (NREGA). I test whether NREGA modulates the impact of adverse weather shocks on yields, and I explore potential mechanisms.

I develop a simple conceptual framework to explore how access to a workfare programme could affect both average yields and the sensitivity of yields to weather shocks. My framework includes a labour market channel, an income/insurance channel and an infrastructure channel. Regarding the labour market channel, I posit that if NREGA creates higher agricultural wages that are less elastic with respect to weather shocks, then this could reduce average yields and increase the sensitivity of yields to weather shocks. Concerning the income/insurance channel, I posit that if NREGA increases household incomes and acts as a form of insurance, this could increase average yields, while having an ambiguous effect on the sensitivity of yields to weather shocks. Regarding the infrastructure channel, I posit that if NREGA improves infrastructure, then this could increase average yields, while making yields less sensitive to adverse weather shocks.

I explore my research question using agricultural data from the Village Dynamics in South Asia Meso dataset (ICRISAT, 2015), merged with gridded daily weather data from the ERA-Interim archive (Dee et al., 2011). I use a difference-in-difference approach that explores the staggered roll-out of NREGA and random, year-to-year variation in weather. I regress crop yields on weather shocks, a NREGA dummy and a vector of NREGA–weather interaction terms, while controlling for district fixed effects, year fixed effects and wide battery of controls. I test for parallel pre-trends by running placebo regressions.

I find evidence that NREGA exacerbates the impact of low rainfall on yields. In my preferred specification, I find that if rainfall is one standard deviation below average, then NREGA reduces yields by 11%, relative to years when the programme was not in place. This increased sensitivity to low rainfall is consistent with an income/insurance channel and a labour market channel. To explore the distributional impacts of my results, I use back-of-the-envelope calculations to benchmark my estimated yield impacts against the expected household gains from NREGA payments, using estimates of NREGA household participation from Imbert and Papp (2015). I find that for households with marginal landholdings, the benefits from NREGA payments exceed the NREGA-induced yield losses. However, for households with medium or large landholdings, the NREGA-induced yield losses may exceed the expected benefits from NREGA payments in years with low rainfall. Coupled with earlier research that has shown that NREGA makes agricultural wages less sensitive to low rainfall shocks (Rosenzweig & Udry, 2014; Santangelo, 2019), my results suggest that NREGA effectively transfers some of the risk of low rainfall shocks away from households that are net sellers of agricultural labour towards households that are net buyers of agricultural labour.

I contribute to three strands of literature. First, I contribute to the literature that explores how off-farm labour market opportunities affect agricultural outcomes. In a seminal paper on India, Jayachandran (2006) finds that adverse rainfall shocks depress the wages of agricultural labourers and that these effects are intensified in locations with less opportunities for migration. Ito and Kurosaki (2009) show that higher levels of weather risk increase the share of off-farm labour supply in India. Looking at Bangladesh, Akram et al. (2017) find that a transport subsidy to encourage migration increases male agricultural wages in the source villages. Dedehouanou et al. (2018) find that increased off-farm self-employment in Niger is associated with higher spending on crop and livestock inputs.

Second, I contribute to the literature that explores the impact of social protection programmes on agricultural productivity. Tirivayi et al. (2016) provide a helpful review of this literature; here, I highlight a few papers of note. In Malawi, Boone et al. (2013) find that a cash transfer programme increases ownership of productive agricultural assets, suggesting that the cash transfers help farmers overcome credit constraints, while Beegle et al. (2017) find that a workfare programme does not lead to increased fertiliser usage. In India, Bhargava (2023) finds that NREGA increases the adoption of labour-saving agricultural technology; Gehrke (2017) finds that after NREGA, farmers plant riskier, but higher return, crop portfolios; and Varshney et al. (2018) find that NREGA does not increase crop yields but that it does increase irrigated areas after a lag. Muralidharan et al. (2021) find that NREGA reduced farm earnings per acre for landowners by 18%, a result they suggest is consistent with NREGA triggering an increase in wages.

Third, I contribute to the literature that explores whether social protection programmes help individuals cope with weather shocks. In Mexico, Adhvaryu et al. (2018) find that a conditional cash transfer programme protects children from early-life rainfall shocks, while Chort and De La Rupelle (2022) find that two social protection programmes—an agricultural cash transfer programme and a disaster fund—mitigate the effect of climate shocks on Mexico–US migration. Shrinivas et al. (2021) find that India's in-kind food transfer programme reduces labour supply and increases wages, with these effects concentrated in years with adverse weather shocks. Looking at NREGA, Dasgupta (2017) finds the programme mitigates the negative impact of drought on childhood health indicators; Ajefu and Abiona (2019) find that NREGA offsets the negative impact of dry rainfall shocks on labour supply; Garg et al. (2020) find that NREGA attenuates the damages of high temperatures on human capital accumulation; and Chatterjee and Merfeld (2021) find that the programme attenuates the relationship between low rainfall and infant sex ratio.

Relative to these strands of the literature, my primary contribution is to estimate the impacts of a social protection programme on agricultural productivity, while explicitly measuring and incorporating weather shocks into the analysis. Rural, agricultural households in LMICs are disproportionately vulnerable to environmental shocks, and yet, they are also the households least likely to be covered by social protection programmes (Allieu, 2019). Furthermore, given agriculture's unique exposure to weather-related risk, it is critical to understand how social protection programmes may modulate the relationship between weather shocks and agricultural productivity, especially in the face of accelerating climate change.

The rest of this paper is organised as follows. Section 2 provides background on NREGA and on Indian agriculture. Section 3 develops a conceptual framework. Section 4 describes the data and presents summary statistics. Section 5 describes the empirical strategy. Section 6 presents the results, and Section 7 discusses their implications. Section 8 concludes.

2 | BACKGROUND

2.1 | Background on NREGA

NREGA is the largest workfare programme in the history of the world. The programme guarantees every rural household in India 100 days of paid work each year. The programme was implemented with a staggered roll-out, with priority given to poorer districts, based on a 'backwardness index' developed by the Planning Commission of India (Planning Commission, 2003). This index was computed using mid-1990s district-level data on agricultural wages, agricultural productivity and the fraction of scheduled caste individuals.[1] The specific timing of the programme roll-out was as follows. In February 2006, 200 districts received access to NREGA (Phase 1). In April 2007, an additional 130 districts were granted access (Phase 2), and in April 2008, the remaining districts received access (Phase 3). Take-up of the programme has been widespread. In 2013–2014, approximately 48 million people worked in the programme, corresponding to roughly 24% of rural households (Desai et al., 2015). The labour generated by the programme is used to build public assets, such as water harvesting structures, irrigation facilities and other community-focussed livelihood infrastructure. Of the public works projects taken up during the FY 2006–2007 and FY 2011–2012, 51% were water conservation and water-related works, including irrigation-related works; 19% were rural connectivity works (e.g. village roads); the remaining projects were mostly works on SC/ST lands or general land development (Ministry of Rural Development, Government of India, 2012).

2.2 | Background on Indian agriculture and agricultural labour

There are two major growing seasons in India: the *kharif* season, which spans June through October, and the *rabi* season, which spans October through February. The top six crops grown in India, by revenue, are rice, wheat, sugarcane, cotton, groundnut and soybeans. Rice, sugarcane and groundnut are grown in both seasons; wheat is grown in *rabi* only; cotton and soybeans are grown in *kharif* only. Wheat, although grown during *rabi*, relies on the monsoon rainfall from the *kharif* season, which affects groundwater and surface water supplies. Weather variability is an important determinant of crop yield variability in India. Ray et al. (2015) calculate that climate variability drives between 26% and 35% of the variability in yields for the major crops, aggregated nationally; for certain crops in certain regions of India, climate variability drives over 60% of the variability in yields. High temperatures tend to reduce crop yields as does low rainfall. High rainfall may be beneficial, detrimental or neutral for yields, depending on the crop.

In addition to affecting crop yields, low rainfall also affects agricultural wages (Jayachandran, 2006). Specifically, in years with low rainfall, there is less output to harvest, so demand for farm labour decreases, and farm wages fall as a result. If labourers can smooth their consumption, then optimally they will work *less* in low rainfall years, which will cushion how much farm wages fall in equilibrium. However, if labourers lack access to savings, insurance or nonagricultural labour markets, then they may in fact work *more* in low rainfall years, which will intensify the drop in equilibrium farm wages. Jayachandran (2006) models these dynamics and finds that agricultural labourers in India have historically been overexposed to weather risk, while landowners have been comparatively insulated from it, due to perverse consumption-smoothing effects that cause labourers to increase their labour supply during low rainfall/low-wage years.

[1]Compliance with the index was imperfect, and some districts received programme access earlier than initially scheduled (Zimmermann, 2021).

Labour scarcity is emerging as a critical constraint to India's agricultural productivity (Binswanger & Singh, 2018; FICCI, 2015; Prabakar et al., 2011; Prasad, 2017; Reddy et al., 2014). Despite increased farm mechanisation, the labour share of the cost of cultivation increased from 1990 to 2015, due to rising real agricultural wages and the imperfect substitutability of human labour and mechanisation (Srivastava et al., 2017). Labour costs represent the single largest component of the cost of cultivation (Srivastava et al., 2017), comprising over 50% of the total variable cost of production for most crops (Ministry of Agriculture, 2016). Agricultural labour is a critical input throughout the growing season, not only at the times of planting and harvest but also throughout the season, for weeding, fertiliser application and other tasks (Agasty & Patra, 2013; Govindaraj & Mishra, 2011; Prabakar et al., 2011). Labour shortages can reduce crop productivity. In the most acute cases, labour shortages can lead to insufficient labour to harvest a standing crop (Biswas, 2018). More broadly, labour shortages can affect the timing of field operations; lead to insufficient weeding or fertiliser usage; or lead to degraded soil fertility, due to insufficient manuring and composting, which can reduce long-term yields (Prasad, 2017). Regarding weeding, weeds compete with crops for nutrients and failure to weed sufficiently can reduce crop productivity (Mani et al., 1968; Van Heemst, 1985). Prabakar et al. (2011) find significant differences in crop yields across farms in India that are affected or unaffected by labour scarcity.

2.3 | Background on NREGA and agricultural labour

Research demonstrates that NREGA increases the average wages of casual workers (Azam, 2012; Imbert & Papp, 2015; Muralidharan et al., 2021), including agricultural casual workers (Berg et al., 2018). Imbert and Papp (2015) find that the daily wages for casual labourers increase by 4.7% in districts with access to NREGA. Berg et al. (2018) find that NREGA increases the *growth rate* of real daily agricultural wages by 4.3% for each year that a district has access to the programme. Berg et al. (2018) infer that increases in NREGA participation over time drive this steady increase in agricultural wages (as opposed to a one-time jump in wages). In addition to increasing average agricultural wages, researchers have found that access to NREGA makes agricultural wages less elastic with respect to rainfall shocks (Rosenzweig & Udry, 2014; Santangelo, 2019). Rosenzweig and Udry (2014) find that NREGA access increases harvest-stage wages by 6% in a year with typical rainfall, but by 15% in a year with an adverse rainfall shock. Similarly, Santangelo (2019) demonstrates that local rainfall has a much smaller effect on local wages, post-NREGA. She estimates that, prior to NREGA, the elasticity between rainfall and agricultural wages was 0.057 and that post-NREGA, this elasticity falls to 0.010. In other words, prior to NREGA, a 10% reduction in rainfall would lead to a 0.57% reduction in agricultural wages, but post-NREGA the reduction in wages would be only 0.1%.

3 | CONCEPTUAL FRAMEWORK

In this section, I discuss mechanisms by which NREGA could affect average yields and affect the sensitivity of yields to weather shocks. I focus on three primary channels by which NREGA, a nonagricultural workfare programme, could affect yields: a labour market channel, an income/insurance channel and an infrastructure channel. These channels are analogous to those described by Berg et al. (2018), but I extend their framework to consider interactions with weather shocks.

3.1 | Labour market channel

As described above, NREGA raises agricultural wages and makes them less sensitive to weather shocks. In this subsection, I explore how changes in wage levels and wage volatility may, in turn, affect yield levels and yield volatility for landowning households.

First, consider the impact of higher agricultural wages on average yields. An increase in agricultural wages is an increase in an input price, which may trigger farmers to purchase less hired labour, apply less household labour and/or reduce spending on other farm inputs. Indeed, Binswanger and Singh (2018) estimate that the short-term elasticity of hired labour with respect to agricultural wages is −0.49: a 10% increase in agricultural wages triggers a 4.9% reduction in hired labour.[2] A reduction in farm labour may reduce crop yields: Binswanger and Singh (2018) estimate that the elasticity of farm output with respect to agricultural wages is −0.12: a 10% increase in agricultural wages leads to a 1.2% reduction in crop output.

Next, consider the impact of wage volatility on yield volatility. As mentioned above, agricultural wages in India fall in years with low rainfall, partially due to decreased labour demand, but also because poor households perversely increase their labour supply in low rainfall years due to consumption-smoothing issues (Jayachandran, 2006). In low rainfall years, the marginal product of agricultural labour is lower than it is in high rainfall years, but it is still positive. In the absence of NREGA, landowners will be able to hire workers in low rainfall years, pay them a low wage and reap the benefits of their labour. But, in low rainfall years in the presence of NREGA, the marginal product of agricultural labour may fall below the NREGA wage rate, so that landowners will be unable to hire workers, and this will exacerbate the negative impact of low rainfall on agricultural yields.

3.2 | Income/insurance channel

A second channel linking NREGA and yields occurs via household income and insurance. Access to NREGA increases the total income of participating households (Bose, 2017; Ravi & Engler, 2015), and NREGA also acts as a form of insurance, since households can rely on it for supplementary income in years with adverse weather shocks (Gehrke, 2017). Higher incomes may increase average yields, if, for example, households invest the money in improved agricultural inputs and assets (Boone et al., 2013). The impact of higher incomes on yield volatility, however, is ambiguous. On the one hand, higher incomes may *decrease* sensitivity, if households can now afford inputs and assets that reduce yield volatility, such as irrigation. On the other hand, higher incomes could *increase* yield volatility, if households become less risk-averse and choose to plant crop portfolios that are higher return but riskier. The insurance-like nature of NREGA could also encourage households to plant riskier crop portfolios or engage in higher risk agricultural practices (Gehrke, 2017).

3.3 | Infrastructure channel

The final channel linking NREGA and yields occurs via the public works infrastructure that NREGA generates, including irrigation projects and roads. Newly created irrigation infrastructure may increase average yields if, for example, it allows farmers to switch to higher-yielding crops that require irrigation. Roads built by NREGA may reduce the prices

[2]Consistent with this labour market channel, Sheahan et al. (2016) find that farm labour during the main *kharif* season decreases due to NREGA.

of agricultural inputs for farmers, which would also increase yields. Regarding the sensitivity of yields to weather, irrigation-related infrastructure may reduce yield volatility, as irrigation protects against temperature and precipitation stress (Taraz, 2018; Zaveri & Lobell, 2019).

4 | DATA

4.1 | NREGA data

I use data from the Ministry of Rural Development on the year each district received NREGA access. I use data from the NREGA Public Data portal on district-level NREGA labour participation rates and expenditures.[3] I use three district-level NREGA take-up measures: the number of NREGA person-days worked; the number of households working the maximum number of days permitted; and NREGA labour expenditure. The NREGA data correspond to the fiscal year (April 1 to March 31) and are available for 2006–2012. Imbert and Papp (2011) show that, prior to the implementation of bank-based wage payments in 2008, administrative NREGA employment reports were significantly inflated relative to survey data, due to corruption issues. To avoid using inflated data, I restrict my take-up regressions to 2009–2012.

4.2 | Agricultural data

I use agricultural data from the Village Dynamics in South Asia (VDSA) Meso data set, compiled by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, 2015). Village Dynamics in South Asia provides data on crop areas, production and revenue for 481 districts, in 19 states, for 1990–2011, based on the agricultural year (July 1 to June 30).,[4][5] I create an aggregate yield measure that weights together the yields for the 18 crops with price data: rice, wheat, sugarcane, cotton, groundnut, soybeans, rapeseed and mustard, chickpea, maize, sorghum, pearl millet, pigeon pea, sesame seed, sunflower, finger millet, castor, barley and linseed.

Following Burgess et al. (2017), I focus on agricultural yields, rather than agricultural revenues. Since agricultural markets in India are not well-integrated, local weather shocks may affect local crop prices as well as affecting yields. As a result, price effects will increase farmers' revenues and, hence, partially offset their yield losses. However, the higher agricultural prices will hurt households that are net consumers of the crops. Thus, to capture losses to both producer and consumer surplus, I analyse yields. I create a composite, price-weighted yield, using average crop prices from base period 2000 to 2004:

$$\text{Aggregate\_yield} = \frac{1}{\text{Total\_area}} \times \sum_{c=1}^{18} \left(\text{Production}_c \times \text{Average\_base\_period\_price}_c \right)$$

where c is the 18 crops in the data. This approach removes the price effects and is used by Pande and Duflo (2007). I also analyse individual crop yields, for the top six crops by revenue.

[3]Accessed at https://mnregaweb4.nic.in/netnrega/dynamic2/dynamicreport_new4.aspx.

[4]In order to match district boundaries as of 2006 (when NREGA was implemented), I use the unapportioned version of VDSA, which creates new districts (with new unique identifiers) in the case of district splits.

[5]Crop areas in the VDSA data refer to areas cultivated, not areas harvested.

TABLE 1 District summary statistics by NREGA phase

	Full sample	Phase 1	Phase 2	Phase 3
Log-aggregate yield (Rs./hectare)	9.567	9.400	9.564	9.701
	(0.513)	(0.432)	(0.510)	(0.529)
Log rice yield (Rs./hectare)	9.493	9.314	9.463	9.658
	(0.588)	(0.584)	(0.586)	(0.545)
Log wheat yield (Rs./hectare)	9.432	9.249	9.412	9.605
	(0.535)	(0.493)	(0.479)	(0.543)
Log sugarcane yield (Rs./hectare)	10.80	10.75	10.77	10.84
	(0.628)	(0.552)	(0.601)	(0.689)
Log cotton yield (Rs./hectare)	9.695	9.629	9.626	9.758
	(0.663)	(0.652)	(0.668)	(0.662)
Log groundnut yield (Rs./hectare)	9.636	9.592	9.670	9.659
	(0.467)	(0.438)	(0.427)	(0.505)
Log soybean yield (Rs./hectare)	9.532	9.465	9.493	9.616
	(0.575)	(0.715)	(0.433)	(0.468)
Harmful degree days (100, C)	21.62	21.25	21.39	21.98
	(5.334)	(4.587)	(5.002)	(6.023)
Total precipitation (100 mm)	10.28	10.94	10.97	9.427
	(4.328)	(4.002)	(4.008)	(4.601)
Log daily wage for agricultural labour (male)	4.190	4.101	4.165	4.276
	(0.237)	(0.196)	(0.139)	(0.276)
Ag output per worker in 2001, normalised	0.0408	−0.321	−0.0540	0.406
	(1.098)	(0.548)	(0.851)	(1.404)
Fraction scheduled caste/scheduled tribe in 2001	0.268	0.353	0.245	0.213
	(0.149)	(0.175)	(0.0954)	(0.111)
Proportion of crop area irrigated in 2005	0.477	0.394	0.517	0.528
	(0.289)	(0.258)	(0.273)	(0.308)
Observations	11,218	3951	2365	4754

Note: Mean coefficients. Standard deviations in parentheses.

The timing of NREGA roll-out was correlated with time-invariant district characteristics. As described in greater detail in Section 5, some of my regression specifications interact linear time trends with these characteristics, as a way to control for trends correlated with these characteristics, following Imbert and Papp (2015). The specific controls I construct are as follows: the fraction of each district's population that is scheduled caste or scheduled tribe in 2001 (from the Census); male agricultural wages in 2005 (from VDSA); and agricultural output per worker in 2001 (from VDSA). I chose these controls because they correspond to the measures that were used to construct the 'backwardness index' that determined the NREGA phases. In addition, I also use VDSA data on the proportion of irrigated land in each district in 2005 (the year prior to Phase 1 NREGA roll-out), since irrigation may affect yield volatility.

Table 1 shows summary statistics for the agricultural variables, by the NREGA phase group. As expected, average yields are higher in the (wealthier) Phase 3 districts. My empirical strategy will include district fixed effects to control for unobserved, time-invariant district characteristics that differ across the phase groups. Figure 1 plots log-aggregate yields over time by phase group and does not reveal any obvious differential trends across groups, prior to NREGA.

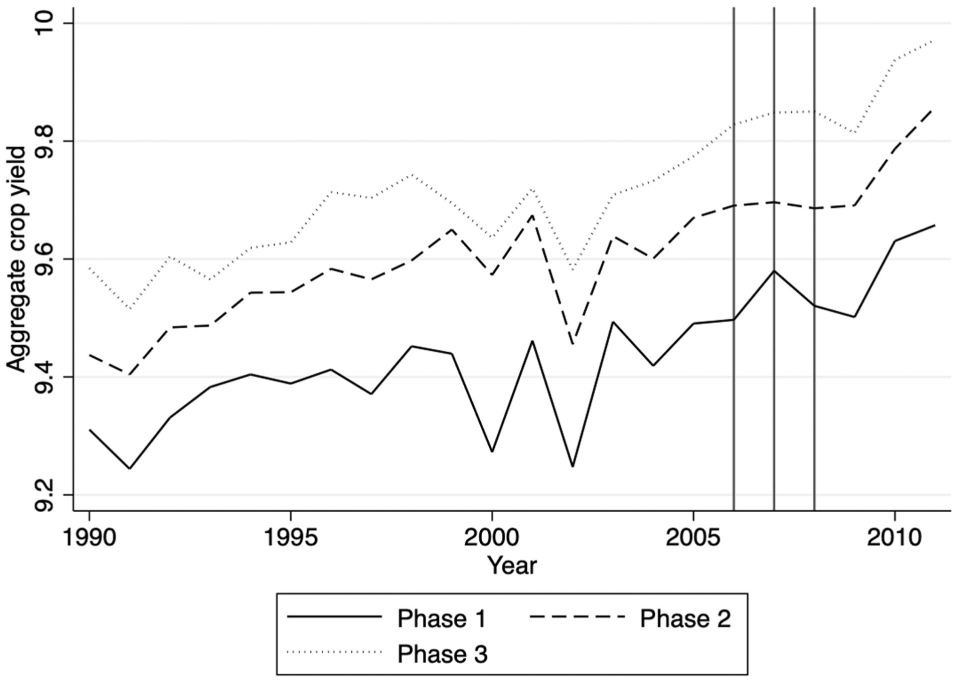

FIGURE 1 Aggregate crop yields, by phase. The figure displays the trends in aggregate crop yields over time, averaged across the districts in each of the three NREGA phase groups. The vertical lines show the year of introduction of NREGA for districts in each phase: 2006 for Phase 1, 2007 for Phase 2 and 2008 for Phase 3.

4.3 | Weather data

I use gridded weather data from the ERA-Interim Archive, a daily reanalysis data set constructed by the European Center for Medium-Ranged Weather Forecasting (Dee et al., 2011). ERA-Interim provides data on total precipitation, average temperature, maximum temperature and minimum temperature over each 12-hour period on a 1° degree by 1° degree latitude–longitude grid, for 1979–2014. To construct district-level daily weather outcomes, I average the weather outcomes from all grid points within 125 km of each district's centroid, using the inverse square root of the distances from the centroid as weights.

I measure temperature using harmful degree days (HDDs), which is defined as:

$$HDD_{Upper}(T) = \sum (T - Upper) \times 1(T > Upper),$$

where T is the observed temperature and *Upper* is a threshold for detrimental temperature. Harmful degree days is a concise heat statistic that effectively captures the impact of high temperatures on crops (D'Agostino & Schlenker, 2016). Harmful degree days captures the fact that, below a certain threshold, higher temperatures may be neutral (or even beneficial) for crops, but that above a certain threshold, higher temperatures become harmful, with a harm that increases roughly linearly with temperature. I construct daily HDD values using the sine-interpolation method (D'Agostino & Schlenker, 2016) and then sum them over the appropriate growing season for each crop. For the aggregate crop yield measure, I use the growing season of June–February.

To estimate the impact of precipitation on yields, I use a piecewise function of rainfall. I first construct a rainfall z-score for each district-year observation—relative to that district's long-run rainfall distribution—by taking rainfall, subtracting that district's mean rainfall and then dividing by that district's long-run standard deviation of rainfall. Average annual rainfall levels vary widely across India, and so it is important to scale by a district's long-run rainfall distribution. Next, I break the z-score into two components: one for above-average rainfall and the other for below-average rainfall. Specifically, *Low_rainfall* is a continuous variable that equals the absolute value of the rainfall z-score, if the z-score is negative, and equals zero otherwise. Similarly, *High_rainfall* is a continuous variable that equals the rainfall z-score if the z-score if positive, and equals zero otherwise. This kinked specification allows for nonsymmetric impacts of above-average versus below-average rainfall.[6] Both rainfall measures are constructed relative to the relevant growing season for each crop, which is June–February in the case of the aggregate crop yield measure.

Table 1 shows the summary statistics for the weather variables, disaggregated by NREGA phase. The Phase 3 districts are, on average, slightly hotter and have somewhat lower precipitation than the Phase 1 and 2 districts.

5 | EMPIRICAL STRATEGY

5.1 | Take-up regression and yield regression

Before estimating the impact of NREGA on the weather–yield relationship, I run two preliminary regressions. First, confirming earlier work, I demonstrate that adverse weather shocks increase NREGA take-up. I estimate:

$$ln\left(Takeup_{jpt}\right) = \theta Weather_{jpt} + \eta_j + \kappa_t + \epsilon_{jpt}. \tag{1}$$

$Takeup_{jpt}$ is the number of NREGA person-days worked in district j, of phase group p, in year t; the number of households that worked the maximum number of days permitted; or the district-level NREGA labour expenditure. I use take-up data spanning 2009–2012. The vector

$$Weather_{jpt} = \left\{HDD_{jpt}, Low\_rainfall_{jpt}, High\_rainfall_{jpt}\right\}$$

controls for weather shocks. Take-up variables correspond to the fiscal year (April 1 to March 31); weather variables in this regression span the same months. η_j is a district fixed effect, capturing time-invariant district characteristics that may be correlated with take-up. κ_t is a year fixed effect, capturing time-specific shocks. ϵ_{jpt} is an idiosyncratic error term. The coefficients of interest are the θ coefficients, which capture the impact of weather on take-up. The identifying assumption for this regression is that, conditional on the year and district fixed effects, year-to-year weather fluctuations are essentially random and should be uncorrelated with other (nonweather) shocks. This assumption is widely used in the climate–economy literature (Dell et al., 2014).

Second, I regress yields on weather, to verify my weather specifications are appropriate:

$$Yield_{jpt} = \zeta Weather_{jpt} + \eta_j + \kappa_t + \epsilon_{jpt} \tag{2}$$

$Yield_{jpt}$ is the log-aggregate crop yield or log individual crop yield (Rs./hectare) and $Weather_{jpt}$ is as above. I use crop yield data from 1990 to 2011. I construct crop-specific weather variables that correspond to each crop's growing season (Appendix S2: Table S1).[7] Different crops may have different heat tolerances. Therefore, for each crop, I estimate the regression separately, using HDD measures with the thresholds of 15°C, 20°C, 25°C and 30°C, and

[6]Burke and Emerick et al. (2016) also use a kinked rainfall specification.

[7]For the aggregate crop yield regressions, I use June–February for the growing season, corresponding to the concatenation of the *kharif* and *rabi* seasons.

choosing the threshold with the best R-squared (as presented in Appendix S2: Table S1). η_j is a district fixed effect, capturing any time-invariant, district-level characteristics that might be correlated with weather or yields and κ_t is a year fixed effect capturing time-specific shocks. As above, the identifying assumption is that, conditional on the year and district fixed effects, year-to-year weather fluctuations are essentially random and should be uncorrelated with other unobservables.

5.2 | Main regressions

To estimate the impact of NREGA on the weather–yield relationship, I use a difference-in-difference strategy that exploits the staggered roll-out of the programme and random year-to-year fluctuations in weather. The difference-in-difference approach has been used widely in the literature to estimate NREGA impacts (Berg et al., 2018; Bose, 2017; Dasgupta, 2017; Gehrke, 2017; Imbert & Papp, 2015; Rosenzweig & Udry, 2014; Sheahan et al., 2016). I estimate:

$$\begin{aligned} \ln\left(\text{Yield}_{jpt}\right) = \alpha\ \text{NREGA}_{jpt} + \beta\ \text{Weather}_{jpt} \times \text{NREGA}_{jpt} + \gamma_p \text{Weather}_{jpt} + \delta \text{Weather}_{jpt} \times t \\ +\ \ \lambda_p \times t + \eta_j + \kappa_t + \epsilon_{jpt}. \end{aligned} \tag{3}$$

where $Yield_{jpt}$ is the aggregate yield in district j, in phase group p and in year t. $NREGA_{jpt}$ equals one if NREGA is active in district j in year t and is zero otherwise. All districts start with $NREGA_{jpt}$ equal to zero and end with $NREGA_{jpt}$ equal to one, with a single switch occurring the year that district got access to NREGA. The subscript $p \in \{1, 2, 3\}$ denotes the NREGA phase groups. The sample is restricted to 2003–2011 and to districts for which the dependent variable is nonmissing in all years. α captures the impact of NREGA on yields in years with average weather, while β captures the impact of NREGA on yield sensitivity to weather. I demean HDD_{jpt} so α captures the effect of NREGA at average levels of HDD_{jpt}.

The term $\gamma_p Weather_{jpt}$ allows the impact of weather on yields to differ across the phase groups. For example, yields in Phase 3 districts may be less sensitive to low rainfall shocks since those districts are richer and better irrigated. Including the phase–weather interaction terms allows for this effect. Note that the term of interest, $\beta Weather_{jpt} \times NREGA_{jpt}$, only turns on in the years that a district has NREGA access, whereas the term $\gamma_p Weather_{jpt}$ is active for all years in the sample. Thus, β captures the *change* in weather sensitivity, post-NREGA roll-out, relative to the normal weather sensitivity for districts in a given phase group.

The term t is a linear time trend, which I interact with the weather vector $Weather_{jpt}$. Interacting weather with a linear time trend allows for weather impacts to vary over time—for example, crop yields might be getting more sensitive to high temperatures over time—and ensures that this effect does not contaminate my estimate of the impact of NREGA on yield sensitivity. I also interact the linear time trend with the phase dummies, to allow for potential differential trends in average yields over this time period, across the three groups, which are unrelated to NREGA. Lastly, I include a year fixed effect and a district fixed effect.

5.3 | Identification assumptions and robustness checks

Now, let us consider the identification of α, which captures the impact of NREGA on yield levels. Equation 3 includes district fixed effects (which allow yield levels to vary across districts), year fixed effects (which allow for yield levels to vary over time) and a linear time trend interacted with the phase dummies (which allows for differential trends in yield levels across phase groups). The identification of α relies on the assumption that, conditional on these controls, there were no other unobserved shocks that affected yields and that occurred precisely in the years that a district had NREGA access. A similar assumption is made in other difference-in-difference NREGA papers (Berg et al., 2018; Bose, 2017; Dasgupta, 2017; Gehrke, 2017; Imbert & Papp, 2015; Rosenzweig & Udry, 2014; Sheahan et al., 2016). Next, let us consider the identification of β, which captures the impact of NREGA on yield sensitivity. Here, the key regression controls are the phase-by-weather interaction terms (which allow weather to have an ongoing different effect in each phase district group) and the trend-by-weather interaction terms (which allow weather impacts to vary over time). The identification of β relies on the assumption that, conditional on this set of controls, there were no unobserved shocks that affected yield sensitivity and that occurred precisely in the years that a district had access to NREGA.

To further explore the robustness of my results, I introduce three sets of additional controls. First, I include some time-invariant controls (Z_j) interacted with a linear time trend (t): agricultural wages in 2005, agricultural output per worker in 2001, the fraction scheduled caste/scheduled tribe in 2001 and the proportion of cropland irrigated in 2005. I include the first three controls, following Imbert and Papp (2015), because similar markers were used to construct the 'backwardness index' that determined the NREGA roll-out. Including these controls interacted with a time trend further controls for the possibility of differential trends by the NREGA phase group. Controlling for irrigation interacted with a time trend allows for the possibility of differential trends in yields across low- versus high-irrigation districts. Second, I interact these time-invariant controls Z_j with the weather vector $Weather_{jpt}$ to allow for the possibility that these controls might affect yield sensitivity. For example, districts with higher pre-NREGA irrigation levels might be less sensitive to low rainfall. Including these interactions ensures that any such effects do not bias the coefficients of interest, α and β. Lastly, I include a triple interaction of the linear time trend, the phase dummies and the weather variables, which allows for that possibility that the districts in each phase group might have differential trends in their sensitivity to weather.

In addition to these controls, I perform a set of placebo tests, to test for pre-trends across the different NREGA phase groups. Specifically, I estimate Equation 3, but with two key changes. First, in place of $NREGA_{jpt}$, which equals one when a district has NREGA access and zero otherwise, I use a placebo indicator, $Placebo_{jpt}$, which is shifted five (or 10) years earlier. That is, $Placebo_{jpt}$ is a dummy indicator that starts out as 0 and becomes one at the point that is five (or 10) years before a district had access to NREGA. Second, correspondingly, I also shift the range of the data used to be five (or 10) years earlier. I expect to find no statistically significant coefficients for $Placebo_{jpt}$ or for $Weather_{jpt} \times Placebo_{jpt}$.

6 | RESULTS

6.1 | Take-up results and yield results

Table 2 presents the results of the take-up regression (Equation 1), with standard errors clustered at the district level.[8] The table shows that higher temperatures have a positive and significant effect on the number of person-days worked and on labour expenditure. Low rainfall has a positive and significant effect on the number of households that are working the maximum number of days and on labour expenditure. These results are consistent with the earlier literature that shows that adverse weather shocks increase NREGA participation (Garg et al., 2020; Santangelo, 2019; Zimmermann, 2021). In terms of magnitudes, a one (within-district) standard

[8]Subsequent tables use Conley standard errors, but the take-up regression, which spans only four years of data, is relatively underpowered and uses district-level clustering.

TABLE 2 Impact of weather shocks on NREGA take-up

	(1)	(2)	(3)
	Log person-days	**Log hhs 100 days**	**Log exp. labour**
HDD	0.0826***	0.0527	0.0983***
	(0.0261)	(0.0410)	(0.0281)
High_rainfall	−0.00536	−0.0305	0.00704
	(0.0306)	(0.0521)	(0.0301)
Low_rainfall	0.0446	0.248**	0.107**
	(0.0396)	(0.103)	(0.0422)
Constant	10.76***	7.804***	7.560***
	(0.0606)	(0.0932)	(0.0655)
Observations	1927	1908	1932
R^2	0.9357	0.0366	0.0342

Note: Standard errors in parentheses. In this table, NREGA data and weather data are both annual and based on the fiscal year, which runs from April through March. Years 2009–2012. Standard errors clustered at the district level. All columns include district fixed effects and year fixed effects.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

deviation increase in HDDs raises NREGA labour expenditure by 12%, while moving from a rainfall z-score of 0 to a rainfall z-score of −1 raises NREGA labour expenditure by 11%.[9]

Table 3 presents the yield regression (Equation 2) results. Here, and in all subsequent tables, I use Conley standard errors (Conley, 1999) that allow for spatial correlation up to 1000 km and arbitrary serial correlation, using Stata routines from Hsiang (2010) and Fetzer (2020). Table S1 presents the growing season months and heat thresholds used for each crop. Table 3 demonstrates that higher temperatures reduce aggregate yields; this effect is statistically significant at the 1% level. For individual crops, the impact of higher temperatures is also negative, with significance levels ranging from 1% to 10%. I do not detect a statistically significant effect of high rainfall on crop yields. Low rainfall significantly reduces aggregate yields—and rice, wheat, cotton and groundnut yields—all at the 1% significance level. A one (within-district) standard deviation increase in HDDs reduces aggregate yields by 2.6%, while moving from a rainfall z-score of 0 to a rainfall z-score of −1 reduces aggregate yields by 7.2%.

Since NREGA was rolled out during this period, a potential concern is that NREGA rollout might be coincidentally correlated with weather shocks, hence biasing this yield regression. In Appendix S2: Table S2, I test for a correlation between NREGA access and my weather variables, conditional on the year and district fixed effects that I use in all regressions. The results are reassuring: conditional on year and district fixed effects, I do not find a statistically significant correlation between NREGA access and weather shocks.

6.2 | Main regression results

Table 4 presents the results of the regressions that allow NREGA to modulate the impact of weather on yields, with additional controls added in each subsequent column. Column 3 matches the regression specification presented in Equation 3, while Columns 1 and 2 have

[9]The average within-district standard deviation for HDDs is 115. Harmful degree days is scaled by 100 in this and all regressions. Thus, the average standard deviation for the scaled HDD variable is 1.15.

TABLE 3 Impact of weather shocks on crop yields

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Aggregate	**Rice**	**Wheat**	**Sugarcane**	**Cotton**	**Groundnut**	**Soybean**
HDD	−0.0285***	−0.0332***	−0.0241**	−0.0282***	−0.0413*	−0.0745***	−0.0615*
	(0.00940)	(0.0112)	(0.0108)	(0.00979)	(0.0225)	(0.0229)	(0.0319)
High_rainfall	0.0185*	0.00393	0.0158*	−0.00950	0.0228	−0.0250	0.00794
	(0.00978)	(0.0132)	(0.00955)	(0.00999)	(0.0201)	(0.0161)	(0.0221)
Low_rainfall	−0.0744***	−0.0786***	−0.0534***	0.0278*	−0.0941***	−0.0935***	0.0220
	(0.0157)	(0.0238)	(0.0128)	(0.0156)	(0.0297)	(0.0248)	(0.0420)
Observations	10,767	10,185	9096	8713	5223	7719	3640
R^2	0.0466	0.0316	0.0201	0.0035	0.0262	0.0353	0.0074

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Years 1990–2011. See Table S1 for the growing season months and heat thresholds used for each crop. All columns include district fixed effects and year fixed effects.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 4 Impact of NREGA and weather shocks on aggregate yields

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**
NREGA	0.0345	0.0702**	0.0687**	0.0682**	0.0406	0.0417*
	(0.0306)	(0.0277)	(0.0281)	(0.0279)	(0.0255)	(0.0250)
NREGA*HDD	0.00319	0.000568	0.000517	0.000454	0.00309	0.00351
	(0.00247)	(0.00375)	(0.00375)	(0.00376)	(0.00326)	(0.00313)
NREGA*High_rainfall	−0.0445**	−0.0418	−0.0416	−0.0411	0.00315	0.00406
	(0.0217)	(0.0310)	(0.0308)	(0.0307)	(0.0328)	(0.0323)
NREGA*Low_rainfall	−0.0879*	−0.203***	−0.201***	−0.198***	−0.161***	−0.159***
	(0.0474)	(0.0596)	(0.0602)	(0.0602)	(0.0541)	(0.0519)
Observations	3564	3564	3564	3564	3564	3564
R^2	0.0780	0.0830	0.0836	0.0862	0.2607	0.2636
Phase × weather	Y	Y	Y	Y	Y	Y
Trend × weather		Y	Y	Y	Y	
Trend × phase			Y	Y	Y	Y
Trend × controls				Y	Y	Y
Controls × weather					Y	Y
Trend × phase × weather						Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log-aggregate crop yield. Years 2003–2011. All columns include district fixed effects and year fixed effects. NREGA is a dummy indicator for access to NREGA. Weather variables are defined in Section 4.3. Controls vary by column. See Section 5 for definitions of the control variables.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

fewer controls, and Columns 4–6 have more controls.[10] The interaction between NREGA and low rainfall is negative and statistically significant in all columns, demonstrating that NREGA increases the sensitivity of aggregate yields to low rainfall. This effect is robust to the inclusion of a wide variety of controls. In terms of magnitudes, and looking at Column 6—my preferred specification—I find that if rainfall is one standard deviation below average, then NREGA reduces yields by 11%, relative to if the programme had not been in place. Considering the channels discussed in Section 3, this increase in sensitivity to low rainfall shocks is consistent both with a labour market channel and with an income/insurance channel. It is not consistent with the infrastructure channel. The coefficient on the NREGA dummy is positive in all columns and statistically significant in three of six. This provides suggestive evidence that NREGA may increase yields in average rainfall years. However, this coefficient loses significance in the most saturated specifications (Columns 5 and 6).

6.3 | Placebo tests

Tables 5 and 6 test the parallel trends assumption, by running placebo tests that mimic the structure of the regressions in Table 4. In place of $NREGA_{jpt}$, which equals one when a district has NREGA access and zero otherwise, I use a placebo indicator $Placebo_{jpt}$ that is shifted five (or 10) years earlier. In Table 5, one coefficient is significant at the 10% level, but since the table includes 24 coefficients, this is comparable to what we might expect to see by random chance. Similarly, in Table 6, only one coefficient is significant, again at the 10% level. In both cases, the inclusion of additional controls wipes out this significance. Taken together, Tables 5 and 6 strengthen confidence that the results in Table 4 are not being driven by pre-existing differential trends across the phase groups.

6.4 | Additional agricultural outcomes

Having analysed yields (Rs./hectare), I look at crop production. Table 7 matches the specifications of Table 4, but the dependent variable is log production, in Rs., using 2000–2004 prices. The pattern of the coefficients is very similar to that in Table 4. The production results—like the yield results—are consistent with the income/insurance channel and the labour market channel.[11] I also run a specification whose dependent variable is revenue per area, using current deflated prices (instead of the base year prices used in the main specification). The results, presented in Appendix S2: Table S4, are consistent with my main specification.

Having analysed aggregate yields, production and revenue, I now look at individual crop yields for the top six crops in Table 8. For concision, I report only the most saturated regression model (e.g. Column 6 from Table 4). The sign on the interaction between NREGA**Low_rainfall* is negative for most crops, including the top three crops by revenue (rice, wheat and sugarcane), but not statistically significant. Other specifications, with slightly fewer controls (e.g. following the format of Columns 3–5 in Table 4), also fail to find statistically significant effects.[12] The failure to detect statistically significant effects for individual crops may be driven by the smaller sample size for these regressions, since not all districts grow all crops.

[10]For concision, Table 4 just reports the coefficients of interest: those on the NREGA indicator and the NREGA–weather interactions. Appendix S2: Table B3 reports a fuller set of coefficients.

[11]Placebo versions of Table 7 find no statistically significant effects of a placebo that is placed five or 10 years earlier than the true NREGA rollout (tables available upon request).

[12]Results are available upon request from the author.

TABLE 5 Testing the parallel trends assumption: Placebo dummy, five years earlier than NREGA roll-out.

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**
Placebo	0.00267	0.0253	0.0296	0.0315	−0.0139	−0.0126
	(0.0343)	(0.0408)	(0.0396)	(0.0393)	(0.0318)	(0.0313)
Placebo*HDD	0.00519	0.00407	0.00398	0.00361	−0.00366	−0.00380
	(0.00369)	(0.00507)	(0.00502)	(0.00487)	(0.00332)	(0.00330)
Placebo*High_rainfall	0.0258	0.0175	0.0116	0.00701	0.0336	0.0304
	(0.0358)	(0.0399)	(0.0401)	(0.0382)	(0.0355)	(0.0363)
Placebo*Low_rainfall	−0.0419	−0.0882	−0.0953*	−0.0882	−0.0595	−0.0596
	(0.0392)	(0.0573)	(0.0568)	(0.0549)	(0.0425)	(0.0418)
Observations	3616	3616	3616	3616	3616	3616
R^2	0.1057	0.1068	0.1084	0.1267	0.3380	0.3390
Phase × weather	Y	Y	Y	Y	Y	Y
Trend × weather		Y	Y	Y	Y	
Trend × phase			Y	Y	Y	Y
Trend × controls				Y	Y	Y
Controls × weather					Y	Y
Trend × phase × weather						Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log-aggregate crop yield. Years 1998–2006. All columns include district fixed effects and year fixed effects. Placebo is a dummy indicator that starts out as 0 and turns to 1 five years before a district had access to NREGA. Weather variables are defined in Section 4.3. Controls vary by column. See Section 5 for definitions of the control variables.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Lastly, I analyse crop areas. In Table 9, the dependent variable is the log-aggregate crop area or the log area of each individual crop. Cropping area decisions are largely made prior to the realisation of the weather shock for that growing season. Hence, in this specification, I include the NREGA dummy term, and the full set of controls, but drop the NREGA–weather interaction terms. I find a statistically significant effect for rice: NREGA access increases rice areas by 6%. I do not find a significant effect for any of the other crops, or for aggregate crop areas. The increase in rice areas is moderately consistent with the income/insurance channel, since rice is a moderately risky crop. The coefficient of variation of rice yields is higher than that of groundnut and of the common grains, although lower than that of sugarcane and cotton (Gehrke, 2017). Thus, this effect could be consistent with an increase in risk tolerance, following access to NREGA. In addition, rice is less labour-intensive that sugarcane, cotton and groundnut, although more labour-intensive than wheat and soybeans (FICCI, 2015). Thus, an increase in rice area could be consistent with a labour market channel, if farmers are switching to rice from more labour-intensive crops.

For completeness, Appendix S2: Table S5 reports the individual crop area regressions, but including the NREGA–weather interactions. These terms are excluded from the main area specification, since cropping decisions are largely made prior to the realisation of the weather shock. Including these terms causes the significance of the NREGA term in the rice area regression to fall from 5% to 10%. The NREGA–weather interaction terms are largely insignificant, as expected, except that for soybean areas, the NREGA–HDD interaction is significant and negative: soybean areas fall more in hot years if NREGA is in place, than when it is not. Soybeans are only grown in about a quarter of the districts in my sample, so I do not emphasise these results too much, but they are broadly sensible. Since soybeans in

TABLE 6 Testing the parallel trends assumption: Placebo dummy, ten years earlier than NREGA roll-out.

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**
Placebo	−0.0298	−0.0167	−0.0208	−0.0183	−0.0371	−0.0384
	(0.0264)	(0.0310)	(0.0302)	(0.0303)	(0.0266)	(0.0267)
Placebo*HDD	0.00436*	−0.000543	−0.000520	−0.000701	0.00200	0.00182
	(0.00243)	(0.00369)	(0.00365)	(0.00367)	(0.00273)	(0.00273)
Placebo*High_rainfall	0.0120	−0.0181	−0.0200	−0.0258	0.0146	0.0173
	(0.0216)	(0.0267)	(0.0270)	(0.0273)	(0.0238)	(0.0240)
Placebo*Low_rainfall	−0.0367	−0.0477	−0.0493	−0.0499	−0.0382	−0.0402
	(0.0445)	(0.0683)	(0.0676)	(0.0667)	(0.0515)	(0.0510)
Observations	3501	3501	3501	3501	3501	3501
R^2	0.0472	0.0497	0.0539	0.0593	0.2140	0.2156
Phase × weather	Y	Y	Y	Y	Y	Y
Trend × weather		Y	Y	Y	Y	
Trend × phase			Y	Y	Y	Y
Trend × controls				Y	Y	Y
Controls × weather					Y	Y
Trend × phase × weather						Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log-aggregate crop yield. Years 1993–2001. All columns include district fixed effects and year fixed effects. Placebo is a dummy indicator that starts out as 0 and turns to 1 five years before a district had access to NREGA. Weather variables are defined in Section 4.3. Controls vary by column. See Section 5 for definitions of the control variables.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE 7 Impact of NREGA and weather shocks on aggregate crop production

	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**	**Aggregate**
NREGA	0.0589	0.0913**	0.0933**	0.0997***	0.0633*	0.0626*
	(0.0400)	(0.0360)	(0.0363)	(0.0362)	(0.0327)	(0.0321)
NREGA*HDD	0.00554*	−0.00222	−0.00216	−0.00223	0.00135	0.00158
	(0.00335)	(0.00436)	(0.00435)	(0.00435)	(0.00373)	(0.00359)
NREGA*High_rainfall	−0.0492*	−0.0562*	−0.0569*	−0.0594*	−0.00183	0.000174
	(0.0280)	(0.0329)	(0.0330)	(0.0337)	(0.0350)	(0.0345)
NREGA*Low_rainfall	−0.139**	−0.206***	−0.208***	−0.230***	−0.191***	−0.183***
	(0.0572)	(0.0740)	(0.0741)	(0.0723)	(0.0646)	(0.0629)
Observations	3564	3564	3564	3564	3564	3564
R^2	0.0829	0.0855	0.0857	0.0999	0.2698	0.2722
Phase × weather	Y	Y	Y	Y	Y	Y
Trend × weather		Y	Y	Y	Y	
Trend × phase			Y	Y	Y	Y
Trend × controls				Y	Y	Y
Controls × weather					Y	Y
Trend × phase × weather						Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log-aggregate crop production. Years 2003–2011. All columns include district fixed effects and year fixed effects. NREGA is a dummy indicator for access to NREGA. Weather variables are defined in Section 4.3. Controls vary by column. See Section 5 for definitions of the control variables.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

TABLE 8 Impact of NREGA and weather shocks on individual yields

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Aggregate	**Rice**	**Wheat**	**Sugarcane**	**Cotton**	**Groundnut**	**Soybeans**
NREGA	0.0417*	0.0144	0.0340	0.0414	−0.00275	−0.0242	−0.0774
	(0.0250)	(0.0442)	(0.0343)	(0.0403)	(0.0790)	(0.0602)	(0.0823)
NREGA*HDD	0.00351	0.00261	−0.00159	−0.00392	−0.00271	−0.000294	−0.0182*
	(0.00313)	(0.00425)	(0.00660)	(0.00676)	(0.0102)	(0.0127)	(0.00976)
NREGA*High_rainfall	0.00406	−0.0361	0.00743	−0.0390	−0.0433	0.0446	0.151
	(0.0323)	(0.0462)	(0.0296)	(0.0383)	(0.0500)	(0.0442)	(0.116)
NREGA*Low_rainfall	−0.159***	−0.0624	−0.0982	−0.0723	0.0986	−0.0741	0.0758
	(0.0519)	(0.0439)	(0.0759)	(0.0766)	(0.132)	(0.0813)	(0.154)
Observations	3564	3231	2844	2448	1557	2637	891
R^2	0.2636	0.1116	0.1292	0.1128	0.1093	0.1052	0.1294
Phase × weather	Y	Y	Y	Y	Y	Y	Y
Trend × phase	Y	Y	Y	Y	Y	Y	Y
Trend × controls	Y	Y	Y	Y	Y	Y	Y
Controls × weather	Y	Y	Y	Y	Y	Y	Y
Trend × phase × weather	Y	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log crop yield. Years 2003–2011. NREGA is a dummy indicator for access to NREGA. Weather variables are defined in Section 4.3. All columns include district fixed effects and year fixed effects controls for phase-by-weather, trend-by-phase, trend-by-controls, controls-by-weather and trend-by-phase-by-weather. See Section 5 for definitions of the control variables.

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 9 Impact of NREGA and weather shocks on crop areas

	(1) Aggregate	(2) Rice	(3) Wheat	(4) Sugarcane	(5) Cotton	(6) Groundnut	(7) Soybeans
NREGA	0.0100	0.0574**	−0.0206	0.0312	−0.0748	0.0398	0.0274
	(0.0100)	(0.0274)	(0.0239)	(0.0485)	(0.0550)	(0.0340)	(0.0667)
Observations	3564	3231	2844	2448	1557	2637	891
R^2	0.1435	0.0958	0.1046	0.0927	0.0903	0.1026	0.1426
Phase × weather	Y	Y	Y	Y	Y	Y	Y
Trend × phase	Y	Y	Y	Y	Y	Y	Y
Trend × controls	Y	Y	Y	Y	Y	Y	Y
Controls × weather	Y	Y	Y	Y	Y	Y	Y
Trend × phase × weather	Y	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses are Conley standard errors using a 1000-km cut-off and arbitrary serial correlation. Dependent variable is log crop area. Years 2003–2011. NREGA is a dummy indicator for access to NREGA. All columns include district fixed effects and year fixed effects controls for phase-by-weather, trend-by-phase, trend-by-controls, controls-by-weather and trend-by-phase-by-weather. See Section 5 for definitions of the control variables.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

India are planted in mid-to-late June (AgriFarming, 2022) and I use a growing season of June to October (inclusive), this means some of the weather shock is observed by the time of planting. Soybeans are sensitive to high temperatures (Schlenker & Roberts, 2009), and they also have the lowest crop profits per acre of the top six crops (FICCI, 2015). Hence, one could imagine high early growing season temperatures decreasing how much area a farmer chose to plant with soybeans, especially in the presence of NREGA-induced higher labour costs.

6.5 | Alternative rainfall specifications

In this subsection, I explore the robustness of my results to an alternative rainfall specification. The existing literature has found evidence of important nonlinearities in the impacts of rainfall on agricultural and nonagricultural outcomes (Jayachandran, 2006; Kaur, 2019; Rocha & Soares, 2015; Shah & Steinberg, 2017). The literature on India, specifically, has often defined positive rainfall shocks to be rainfall above a given district's 80th percentile and negative rainfall shocks to be rainfall below a given district's 20th percentile (Jayachandran, 2006; Kaur, 2019; Shah & Steinberg, 2017). In Appendix S2: Table S6, I test the robustness of my results to using this alternative rainfall measure. Reassuringly, the results in Appendix S2: Table S6 are very similar to my main rainfall specification, in terms of signs, significance and effective magnitude.

7 | DISCUSSION

In this section, I discuss three broader points related to my results. First, it is somewhat surprising that in Table 4 I detect an impact of NREGA on yield rainfall sensitivity, but not on yield temperature sensitivity. The channels posited in my conceptual framework should theoretically affect sensitivity to both temperature and precipitation and, furthermore, Table 2 shows that both low rainfall and high temperatures increase NREGA take-up. The yield regression results in Table 3 provide a possible explanation for this discrepancy. A one standard

TABLE 10 Magnitudes of NREGA yield gains or losses versus direct payouts

Weather scenario	Crop profit gains or losses (area = 0 ha)	Crop profit gains or losses (area = 0.5 ha)	Crop profit gains or Losses (area = 7 ha)	Gain from NREGA Payments
Rain z-score = 0	0 INR	297.6 INR	4167.1 INR	874.7 INR
Rain z-score = −1	0 INR	−773.6 INR	−10,831.4 INR	974.4 INR
Average effect	0 INR	−42.3 INR	−593.4 INR	957.5 INR

Note: The first row represents the value for crop profits gains/losses or NREGA payments if a district's rainfall is at its historical average. The second row represents the same values, but for years when a district's rainfall is one standard deviation below its historical average. The third row represents the impacts averaged over the entire observed distribution of weather. The calculations use the coefficients from Table 4. For more details on their construction, see Section 7 and Appendix S1.

deviation increase in HDDs reduces yields by 2.6%, whereas a one standard deviation decrease in rainfall reduces yields by 7.2%. It is possible that the impact of NREGA on yield temperature sensitivity is harder to detect, simply because yields are more sensitive to rainfall than to temperature, at least in the specification used in this paper. Low rainfall and high temperatures are positively correlated in my weather data, so collinearity issues may be another reason why I fail to detect impacts on yield temperature sensitivity.

Second, my estimation strategy assumes that the impact of NREGA on yields is static. In reality, impacts might vary over time: Berg et al. (2018) find that NREGA-induced growth in real agricultural wages increases over time; Varshney et al. (2018) find that NREGA increases irrigation, but only after a lag. The limited time span of the VDSA unapportioned data (which ends in 2011) inhibits an exploration of dynamic effects in this paper, but this is a fruitful area for future research.

Finally, it is useful to compare the magnitude of my estimated yield impacts against the magnitude of the NREGA payments to households, to find the net effect of the programme for households. I do these calculations for three benchmark sets of households: landless labourers, marginal landowning households (cultivating 0.5 hectares) and medium–large landowning households (cultivating seven hectares). For each group, I use the estimates from Table 4 to calculate the impact of NREGA on crop profits in a regular rainfall year and in a low rainfall year. Similarly, I use data on NREGA benefits from Imbert and Papp (2015) and my results on the responsiveness of NREGA take-up to weather from Table 2 to estimate the expected NREGA payments to households in a regular rainfall year and in a low rainfall year. Appendix S1 provides more details on these calculations. The result of this analysis, presented in Table 10, shows that for marginal households (cultivating 0.5 hectares), the reduction in crop profits induced by NREGA is strictly less than the expected benefits those households accrue from NREGA participation. For medium and large landholders (cultivating seven hectares), the expected benefits from NREGA participation also dominate the expected reduction in crop profits. But, for medium and large households, the NREGA-induced yield losses in low rainfall years are substantially greater than the expected benefits from NREGA participation in low rainfall years. This suggests that NREGA increases the weather risk exposure for households that are net buyers of agricultural labour.

8 | CONCLUSION

Public works programmes are growing in popularity in the global South (Gehrke & Hartwig, 2018). It is essential to understand the impact of these programmes on weather-related agricultural risk—especially in the face of accelerating climate change (World Bank, 2015). In this paper, I use a difference-in-difference approach to study how NREGA, a large-scale workfare programme, modulates the relationship between weather and crop yields. I find evidence that NREGA access decreases yields in years with below-average rainfall. My conceptual framework posits that these results are consistent with two channels: an income/insurance channel, whereby NREGA income allows farmers to make higher risk, but also higher return, agricultural decisions; and a labour market channel, whereby NREGA increases agricultural wages, especially in low rainfall years, leading to reductions in crop yields. This NREGA-induced increase in yield sensitivity to low rainfall is of practical importance. As extreme weather events become more frequent under climate change, farmers will be exposed to higher levels of weather risk, and, hence, it is critical to understand how social protection programmes may modulate weather risk. For an individual household, the NREGA-induced increase in yield sensitivity may (or may not) be offset, by direct NREGA payments and/or by NREGA's general equilibrium effects on wages and other economic outcomes.

The distributional implications of my results are also important to consider. Imbert and Papp (2015) note that, beyond NREGA's direct cash transfers, the programme's general equilibrium wage effects amount to a significant redistribution of surplus from households that are net labour buyers to households that are net labour sellers. My results are complementary and suggest that NREGA access also importantly shifts the burden of weather risk from households that are net labour sellers to households that are net labour buyers. Prior to NREGA, casual labourers had limited outside options and, hence, bore a disproportionate share of the weather risk, due to perverse consumption-smoothing labour supply effects in the presence of adverse weather shocks (Jayachandran, 2006). NREGA access, however, reduces the volatility of agricultural wages to rainfall (Rosenzweig & Udry, 2014; Santangelo, 2019), but increases the volatility of crop yields to rainfall, as this paper has shown. The combined impact of these results is a partial shifting of weather risk, from net sellers of agricultural labour to net buyers of agricultural labour.

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DATA AVAILABILITY STATEMENT

Data and code are available from the author upon request.

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SUPPORTING INFORMATION

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