Do Workfare programs affect Agricultural Risk through Crop Choice? Evidence from India

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Abstract

Workfare programs such as India's National Rural Employment Guarantee Scheme (NREGS) are an attractive way to better target consumption smoothing in the face of increasingly extreme weather events driven by climate change. Using the rollout of NREGS across districts in India with quasi-exogenous variation in yearly weather, I document increased volatility of crop yields after implementation of NREGS, with additional yield losses of 8% during a bad rainfall year post-NREGS. In order to test whether these results can be explained by the choice of higher-yielding but more volatile crops but due to the insurance properties of NREGS, I construct novel agricultural risk indices using pre-NREGS moments of district crop revenue distribution. Higher risk as measured by these indices is associated with higher crop yields in good rainfall years, but lower yields after negative rainfall shocks, therefore capturing meaningful features of aggregate risk in crop choice. Using the rollout strategy, I find little evidence that the increased sensitivity can be explained by these measures of risk in crop choice. On the other hand, I find that NREGS strongly dampens pro-cyclical wage response to low rainfall shocks, potentially exacerbating the yield effects of productivity shocks by increasing labor costs. Finally, higher provision of NREGS after a negative rainfall shock worsens yield losses if a negative rainfall shock is also realized next year, but improves yields if a positive shock is realized instead. Policymakers considering such programs should pay close attention to the negative and positive complementarities between social protection and agricultural productivity that these results suggest.

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1 Introduction

Agriculture is the largest source of livelihoods in most low and middle-Income Countries (LMICs). Weather risk is a pervasive feature of agriculture in these settings, with the effects of climate change set to make this risk worse in the future decades (Hallegatte et al. 2016). The lack of insurance against such weather risks leads to substantial welfare losses (Dercon 2002), reduces agricultural productivity (Cole and Xiong 2017) and inhibits productive investments (Morduch 1995). How would indemnifying income risk from weather shocks affect aggregate agricultural output? This paper analyzes the effect of large-scale workfare programs, which reduce income risk for vulnerable populations, on aggregate agricultural yields, and investigates whether risk in crop choice can explain the observed effect.

Workfare programs provide livelihood support to the poorest, particularly after income losses from events such as adverse weather shocks. Their self-targeting mechanism makes these program attractive in the absence of unemployment insurance in fiscally-constrained LMICs (Ravallion 1991; Besley and Coate 1992; Bertrand et al. 2021). Such programs are also increasingly being considered part of a flexible climate adaptation strategy (Rigolini 2021), given that private adaptation may be limited (Burke and Emerick 2016; Taraz 2017, 2018; Fishman 2018). The National Rural Employment Guarantee Scheme (NREGS) in India is the largest such program in the world, promising at least 100 days of minimum wage manual work to each household that demands it.

This paper documents the effects of NREGS on the volatility of agricultural yields. I combine the standard identification strategy in the NREGS literature that relies on the rollout of the program across Indian districts with exogenous yearly weather shocks, controlling for time trends and also making use of a first difference specification. The program decreases aggregate yields by an additional 10% after a negative rainfall shock, the same magnitude of yield loss to a similar rainfall shock pre-program. This effect is precisely estimated and is consistent across various specifications including the first differences specification that performs better for strongly non-stationary data (Wooldridge 2010).

Next, I investigate whether aggregate risk in crop choice is a potential mechanism that could explain the additional volatility. Most small and medium-sized farm-households provide some labor to the agricultural labor market in India, apart from cultivating their own fields; the smallest farm-households are net sellers of labor.[1] The NREGS literature documents substantial increases in prevailing wages for manual farm labor, using both natural experiments (Imbert and Papp 2015; Berg et al. 2018) and RCTs (Muralidharan, Niehaus, and Sukhtankar 2016). This general equilib-

[1] The median farm size in India is extremely small at 0.9 acres, leaving substantial family labor available for hire on the agricultural market.

rium increase in agricultural wages driven by NREGS increases expected earnings for these small farm-households. Through the consumption smoothing opportunities available in the event of agricultural productivity shocks, NREGS can act like social insurance. The provision of such insurance may therefore induce small and medium farm-households to take on additional agricultural risk. Given that most farm-households are smallholders in India, this increase in individual risk could affect aggregate risk.

In order to test this mechanism, I construct novel indices of aggregate risk using pre-NREGS moments of the district crop revenue distribution. District-crop area shares for later years are used to aggregate each of these three moments into three separate indices. Yearly variation in these indices comes from changes in the district-level crop mix. For example, a relative increase in area under crops with higher standard deviation of pre-NREGS revenue would increase the Risk Index of Crop Choice constructed using the second moment (RICC-SD). I show that these indices have skill in predicting variation in realized crop revenue. For example, higher risk in crop mix as measured by RICC-SD is positively correlated with realized crop revenue in normal weather years, but decreases realized revenue in years with bad rainfall or higher than normal temperatures, and increases realized revenue during a good rainfall year. These findings build confidence that these risk indices are meaningful measures of aggregate crop choice.

Using the standard NREGS identification strategy reliant on rollout across districts, I find no evidence of changes in aggregate risk as measured by risk indices constructed from the first and third moments of pre-program crop revenue. I find that the risk index constructed using the second moment increases very slightly by 0.08% after NREGS, indicating a minuscule shift in cropped area toward more risky crops. But, this increase can only explain less than 1% of the net additional effect of NREGS on the rainfall sensitivity of crop yields. Therefore, aggregate risk in crop choice, as measured by the risk indices I construct, does not seem to be driving the increased rainfall sensitivity.

The labor market channel might help explain the effects. Imbert and Papp (2015) find average wage increases of about 8% due to NREGS while Muralidharan, Niehaus, and Sukhtankar (2016) find that beneficiary households' earnings increase by about 14%. These are large effects of a similar magnitude to the estimates for increased sensitivity of crop yields. I further confirm findings in (Rosenzweig and Udry 2014; Santangelo 2019) that wages become less elastic (by about 5.5%) to rainfall shocks after NREGS. This inability to modulate wages in a pro-cyclical manner after a bad rainfall shock may increase labor costs enough for some larger farm-households that it could hurt output during harvest; it may also cause some smaller farm-households to abandon their own crop in order to earn higher incomes on the private labor market.

Two other channels through which NREGS might affect agricultural outcomes are the provision of community infrastructure such as irrigation through public works, and higher use of inputs such as fertilizer due to an alleviation of credit constraints. Neither of these channels would explain why crop yields worsen with negative rain shocks after NREGS; better irrigation would make yields *less* sensitive to rainfall shocks while higher fertilizer usage would increase expected yields without affecting volatility.

This paper contributes to the limited literature on the impact of workfare programs on agricultural outcomes. Firstly, in parallel with (Taraz 2021), this paper documents increased rainfall sensitivity of crop yields post NREGS. This paper builds further confidence in the increased sensitivity result by using two years of additional data as well as a first difference specification that deals better with non-stationary data. But this paper also explicitly analyzes aggregate risk in crop choice as a potential mechanism, finding that it is unlikely to explain the increased crop yield sensitivity. Secondly, I use a nationwide data set of total agricultural output relative to the existing literature on the impact of NREGS on agriculture which focuses on data from one state (Gehrke 2019) or a representative sample rather than complete population from administrative data (Deininger, Nagarajan, and Singh 2016).

Thirdly, I contribute to the small literature on crop choice and climate change by constructing a novel measure of aggregate risk in crop choice. Most papers in this literature use discrete choice models to understand the determinants of cropping patterns (Seo and Mendelsohn 2008; Wang et al. 2010; Kurukulasuriya and Mendelsohn 2008). An exception is Auffhammer and Carleton (2018) who study the impact of crop diversity on drought resilience. In contrast to the literature using discrete choice models, I utilize OLS regressions with a transparent identification strategy. I also study crop choice as an optimal risk-taking response to NREGS-as-insurance that might cause increased yield volatility, relative to other literature which studies crop choice as a climate adaptation margin.

The rest of the paper is structured as follows: section 2 describes the workfare program, section 3 surveys related NREGS literature, section 4 discusses a theoretical framework, section 5 describes data sources and construction of outcomes, section 6 relates the research design, section 7 presents the results and section 8 concludes.

2 Background

2.0.1 The workfare program

The NREGS program was created through an Act of Parliament in 2005 that provided a legal right to employment on labor-intensive public works on demand to each rural household for a minimum of

100 days. The key feature of the program is that it provides a minimum of 100 days of employment per household on demand on public works activities. It incorporates labor-intensive minimum wage work requirements such that individuals with a high opportunity cost of time select out (Besley and Coate 1992). The local administration is supposed to provide work within 5 km of home and 15 days of application.

The program was introduced in phase I to the poorest 200 districts in February 2006, followed by the next poorest 130 districts in phase II (February 2007) and the remaining districts in phase III (April 2008). The assignment of district to phase was based on a "Backwardness Index" created by the Planning Commission using data from the early 1990s. Variables that were used to determine this index along with the weights are available online[2]. The actual assignment of districts to phases did not perfectly follow the index since there was a lot of political bargaining over the large budget allocation to the program. For instance, each state had to have one district in each phase, regardless of the rank of the district. Hence some poor districts in rich states got the program over a poorer district which is among the richest ones in a poor state.

In 2010-2011, 2.3 billion person-days of employment was generated among 53 million households. The budget for that year was Rs 345 billion (US$1.64 billion, 0.6 % of GDP). 60% budget of the total budget is supposed to be for wages and 33% of work is reserved for women at an equal wage to men. Among the projects to be undertaken as part of the program, water management is a major goal. This includes micro-irrigation works, drought-proofing and flood-proofing. The local village council approves projects in consultation with block and district administrations.

The program comes with exhaustive and detailed operational guidelines that run to over 200 pages[3]. This does not preclude further ad-hoc documents that govern aspects of the program separately. A common finding in the literature on NREGS within economics, political science and other related social sciences is the heterogeneity in implementation of the program. Some reasons for this in the literature include the varying nature of labor market conditions and need for public employment, differing administrative and fiscal capacities of states, local elite control and politician-bureaucrat dynamics (Sukhtankar 2017).

2.0.2 Related literature

Evidence on the impact of NREGS on agricultural output and yields are thin compared to the evidence on labor market, consumption, education and other development outcomes. The few articles on this topic are reviewed next. Gehrke (2019) uses panel data from the Young Lives study in

[2] The variables include the fraction of lower castes (constitutionally protected underprivileged groups), agricultural productivity per capita and log casual agricultural wage respectively

[3] https://NREGS.nic.in/Circular_Archive/archive/Operational_guidelines_4thEdition_eng_2013.pdf

Andhra Pradesh to show that households use more inputs on cotton (a commercial crop which is more risky than food grains such as rice) after the introduction of NREGS. Deininger, Nagarajan, and Singh (2016) use household panel data from the Additional Rural Incomes Survey and Rural Economic and Demographic Survey (ARIS/REDS) to similarly show that area devoted to rice goes down even as area under high value crops go up. They also show that percentage irrigated area and input usage increase along with the number of crops planted in all cropping seasons. These papers make the argument that the implicit insurance provision in NREGS allows small farmers to diversify crop portfolios by growing more risky crops and also increases the number of crops being planted in all the cropping seasons. Santangelo (2019) utilize nationally representative employment data to show that the relationship between rainfall shocks and agricultural yield does not change after introduction of the NREGS but that rural wages are no longer pro-cyclical, i.e., NREGS weakens the impact of rainfall shocks on local rural wages. Further, Bhargava (2013) uses agricultural census data to show that smaller farmers are more likely to adopt mechanical technologies in response to rising wages.

In the paper that is closest to my study, Taraz (2021) documents increased volatility of aggregate yields to rainfall shocks after NREGS comes into force, using the same district agricultural output panel data set that I employ. Her findings for the increased sensitivity are of a similar magnitude to those found in this paper. In contrast to Taraz (2021), I extend the analysis to include two additional years of data to 2013. In contrast to their usage of a standardized precipitation variable for rainfall shocks, I utilize the definition of rainfall shock as a dummy based on deviations from historical records (uses the) that has been widely used in the literature on wage determination in Indian village economies (Jayachandran 2006; Kaur 2019). While results are similar in both cases, the use of a dummy allows easier comparison with the previous literature. More importantly perhaps, Taraz (2021) does not test any potential mechanism, only suggesting that various possible mechanisms could explain the result. I develop novel measures of risk in crop choice and proceed to show that increased risk, as measured by these indices, does not explain much of the increased crop volatility.

While the consensus in the literature is that NREGS has increased rural wages, whether this is due to productivity increases or increased market competition for labor is unexplored (Sukhtankar 2017). There is also considerable evidence that NREGS may have crowded out private labor supply (Azam 2012; Imbert and Papp 2015; Berg et al. 2018; Muralidharan, Niehaus, and Sukhtankar 2016). There is some disagreement about which parts of private work declines - most of the evidence suggests that the fall in private sector work may represent a fall in disguised unemployment, idle time or private work with close to zero productivity but Deininger, Nagarajan, and Singh (2016) find that on-farm self-employment increases. All but one of these papers utilize a difference-in-differences strategy that arises from a phased rollout of the program but use various data sources. Imbert and Papp (2015) and Azam (2012) use the National Sample Survey data, Berg et al. (2018) use the Agricultural Wages data from the Indian Ministry of Agriculture while Deininger, Nagarajan, and Singh (2016) use the ARIS/REDS household panel data. Muralidharan, Niehaus, and Sukhtankar (2016) run an RCT in the state of Andhra Pradesh that evaluates the impact of a reform of the NREGS delivery system in the state of Andhra Pradesh. Hence they are able to collect their own data with experimental variation in the improvement of NREGS implementation.

As mentioned earlier, there exists a vast literature on the impact of NREGS on other development outcomes. The reader is referred to the excellent survey by Sukhtankar (2017) for an exhaustive appraisal.

3 Theoretical Framework

This paper investigates whether NREGS makes crop yields more sensitive to weather shocks, and whether this finding can be explained by increased aggregate risk in the district crop mix. I now provide a theoretical treatment of these questions below and discuss the resulting testable hypotheses.

3.1 Risk in crop choice

Risk in production decisions is an important characteristic of the environment for rural farmers in developing countries.[4] These farmers are usually characterized as risk-averse given that they are extremely poor and lack reliable consumption smoothing in the event of productivity shocks. Such risk aversion may cause farmers to plant lower yielding crops that also carry lower output risk. Insurance for output risk could enable such risk-averse households to make more optimal crop choice decisions; but such insurance is usually not available. This insurance market failure can lead to the perpetuation of a low productivity equilibrium (Cole and Xiong 2017; Morduch 1995).

The bulk of agriculture in India is carried out by small farm-households; the median household farm size is about 0.9 acres (Kaur 2019). These households are more likely to be net sellers on the agricultural labor market (Imbert and Papp 2015). NREGS increases the net incomes of such farmers by providing work during the lean season and in the aftermath of a poor monsoon. This

[4] This includes both output and price risk - in this paper, I consider output risk only since price-fixing mechanisms such as government Minimum Support Prices (MSP) are a common feature of this setting, in theory limiting the price risk faced by farmers.

provision of work at close to or higher than agricultural wages introduces an entirely new consumption smoothing mechanism. Thus NREGS can be interpreted as a public insurance program that can more than supplements net incomes when agricultural productivity is low. Muralidharan, Niehaus, and Sukhtankar (2016) show, in an RCT, in the state of Andhra Pradesh that average earnings of a rural household increase by 14%, with 2/3rd of the gains coming from the general equilibrium wage increases which benefit small farm-households the most. These are large effects that could raise expected incomes substantially.

Viewed from the lens of portfolio choice theory, this provision of insurance to risk-averse farmers could lead them to take on higher risk in their crop choice portfolio. Higher risk may be individually optimal in this setting given the insurance market failure that forces the choice of lower risk portfolio in the first place, and could increase expected aggregate yields within district. But higher risk could increase the volatility of yields by making aggregate yields more sensitive to adverse weather shocks.

3.2 Other mechanisms

A few other mechanisms have been postulated in the literature for how NREGS could affect aggregate yields and the weather sensitivity of yields. This paper limits itself to testing the Crop Choice mechanism. But I provide a short summary of these other mechanisms below.

3.2.1 Labor market channel

Before NREGS, weather-driven negative productivity shocks would not change market labor supply or would even *increase* it, since labor was the only economic resource small farmers could sell to smooth consumption (Jayachandran 2006). Larger landowners may have benefited from the procyclical downward wage adjustment that occurs when labor demand decreases while labor supply does not.

An important general equilibrium effect of NREGS is the increase in agricultural wages documented in the literature. At the same time, agricultural wages may become less elastic to negative productivity shocks after NREGS (perhaps because the program creates an outside option that may reduce the monopsony power of village landowners) (Santangelo 2019). Nominal wage rigidities in Indian village labor markets documented by Kaur (2019) can further solidify any level increases in the agricultural wage due to NREGS, and reduce counter-cyclical wage responses to productivity shocks.

This increase in the wage level may negatively affect crop yields if farmers who are net buyers of labor cannot afford to hire more expensive labor during harvest, or if availability of labor is constrained. Farmers that are net sellers of labor may shift labor supply away from own-farms if their outside earnings are higher than the shadow wage on their own farm. Secondly, yield losses from a weather shock could be exacerbated after NREGS if wages do not adjust downward, thereby further increasing labor costs and decreasing labor availability. In the long run, some farmers may adjust to higher costs by increasing mechanization or diversification into non-agricultural activities, avenues that are usually not available to smaller farmers (Bhargava 2013).

I provide some corroborating evidence on the labor market impact of NREGS that confirms existing findings of an increase in wages. The labor market mechanism would result in lower expected yield while making yields more sensitive to adverse weather shocks.

3.2.2 Insurance channel

While the effects of NREGS-as-insurance on crop choice are detailed above, this channel could also affect other agricultural practices such as the adoption of more resilient seeds or better inputs. While mechanization can be seen as a response to increasing wages, the procurement of high fixed cost machinery could also be enabled by the higher incomes that small and medium farmers earn from NREGS. These mechanisms would increase expected yield but also make yields *less* sensitive to weather shocks

3.2.3 Infrastructure channel

Decisions on the public works programs to be undertaken under NREGS are supposed to decided by the local community; in practice this is rarely the case, with a top-down approach more common (Khera 2011). While corruption and misuse of funds under NREGS were documented in the earlier years (Dutta et al. 2012), administrative reforms including better monitoring mechanisms through the use of MIS systems were gradually instituted. If such public works lead to better community-level provision of productive infrastructure such as irrigation facilities or flood protection mechanisms, the level of yields would increase while decreasing yield sensitivity. These mechanisms would also reduce sensitivity of yields to weather shocks while increasing expected yield.

4 Data

4.1 Agricultural outcomes

While the ideal outcome measure to use would be farm-level profits for each crop over time, such data are seldom available for any country. Therefore, I rely on aggregate measures at the district level in India compiled by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in their District Level Database (DLD).[5] This data contains information on crop area planted, output and prices for all the main crops as well as some peripheral crops. Price data is available for 16 crops, covering about 79% of all area under cultivation. This data contains 571 districts across 20 states from 1990-2015 for the agricultural year that runs from July 1 to June 30. I describe the construction of the outcome measures to capture aggregate crop yield and risk in crop choice below.

4.1.1 Measure of crop yields

The main measure is a crop area-weighted sum of the revenue value of output per hectare for each crop ("Revenue Value of Yield" or RVY). Since price data is patchy, I construct single national prices for each crop from pre-program data. All price data used in the analysis pertains to these single national prices. This measure of crop yields captures aggregate crop yield in a single index. This measure has been used widely in the literature to capture output losses without being affected by changes in prices (Duflo and Pande 2007; Burgess et al. 2017; Taraz 2021).

Indian agricultural markets are heavily regulated including through the Minimum Support Price (a floor on crop prices); these markets are also typically not well-integrated across district. These forces can cause prices to move in opposite directions, with trade frictions compensating farmers for some of the crop output losses through higher prices. But the Revenue Value of Yield captures the output loss that is the focus of this paper, leaving price effects out. I also make use of a crop area-weighted output per hectare as a second measure that does not utilize price data.

4.1.2 Measure of risk in crop choice

Output risk is a major issue for farmers in response to negative productivity shocks; higher prices can only compensate for part of the losses due to such shocks. To capture this output risk, I calculate the first three moments of Revenue Value of Yield (RVY) for each crop using data from before

[5] http://data.icrisat.org/dld/src/crops.html

2003. Each of the three measures of risk index of crop choice for each district-year from 2003 onward are then constructed through weighted sums of these three moments for each crop, with the weight being the yearly share of area planted under each crop in that district. The distribution of pre-program RVY is calculated per crop in a contiguous region that shares similar agricultural characteristics, striking a balance between sample size and variation across districts. These moments capture relative crop risk within each region.[6]

The volatility of an asset is usually measured with the second moment of its distribution. The Risk Index of Crop Choice constructed using the second moment ("RICC-SD") can be interpreted as measure of expected volatility of revenue from the district crop mix. Assets with higher returns also tend to be more volatile; this is also true of crop revenues. For this reason, the RICC-Mean and RICC-SD are strongly correlated. I also study whether farmers switch to crops with more outliers using the skewness of pre-program RVY. A positively skewed distribution tends to have more positive outliers than a normal distribution. In other words, returns from these crops are likely to be relatively higher with good rainfall. The skewness of assets is a major consideration in the financial economics literature. For example, Mitton and Vorkink (2007) find that underdiversified investors have a preference for positively skewed stocks; Barberis and Huang (2008) show that a positively skewed security can be "overpriced" and can earn a negative average excess return; and Zhang (2018) demonstrates that Swedish retail investors with lower wealth or labor incomes that have higher downside risk tend to seek investment portfolios with higher skewness

An important point to note is that such changes reflect only yield variation and not price variation, since single national prices are used to construct pre-program moments of the Revenue Value of Yield across regions. Since the moments for each district-crop are fixed at pre-program levels, yearly changes in RICC comes from changes in the area planted under various crops.

Figure 1 plots the variation in the revenue value of yield and the three measures of risk in crop choice over the sample period, separately for the three NREGS phase districts. Only the revenue value has a growth trend across the sample period.

Figure 2 plots the mean for the distribution of crop-region revenue value of yield between 1990-2002 against the SD of this distribution. The figure reflects the fact that a more volatile crop that carries higher risk also has higher reward, although it also comes at a higher cost of inputs.

[6] There are an average of 4.8 districts per region. I also conduct robustness using moments from each crop-state combination. The results are presented in the appendix.

4.2 Wages

This paper does not extensively test for the labor market channel. However, I do provide corroborating evidence to the wage increase with NREGS as well as the reduced weather sensitivity of wages to productivity shocks post-NREGS. The data used is described in this section.

The National Sample Survey on Employment and Unemployment (NSS EUE) is the main source of information on labor conditions including wages and employment in India. I make use of the NSS EUE rounds from years 2003, 2004, 2005, 2007, 2009 and 2011 respectively. This survey provides a detailed break-up of the time spent by activity status of each individual in the survey for the 7 days prior to the survey date. The survey covers every member of the household, regardless of age.

I follow Imbert and Papp (2015) in limiting the sample to individuals aged 18-59 to construct the wage data. Public works employment on NREGS is the closest substitute to "casual labor," which is usually work done on a daily wage rate on spot labor markets. The NSS EUE differentiates such casual work with a separate activity status. I create casual labor wages using this activity status, constructing daily rates for each individual between 18-59 years of age.

4.3 Weather data

4.3.1 Heating degree days

I calculate heating degree days (HDD) for each district-year separately for the planting season and growing season using the ERA5 reanalysis dataset from the European Center for Medium Range Weather Forecasting (ECMWF).[7] This measure of heat exposure is a metric proposed in the agronomic literature, and has been commonly used to capture crop output losses from total excess heat exposure on each growing plant organism (D'Agostino and Schlenker 2016; Burke and Emerick 2016; Colmer 2021). The basic idea here is that temperatures up to the threshold might not hurt the organism or might even be beneficial, but above the threshold the organism suffers harm that is captured well through a linear approximation in total temperature exposure above the threshold. The HDD measures the number of heating degree-days above a threshold during a particular period of time.

$$HDD_{Threshold}(T) = \sum_{season} (T - Threshold) * \mathbb{1}(T > Threshold)$$

[7] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

ERA5 provides hourly data on temperature at 30 km resolution for the whole world from 1979 onward. I follow the literature in using the sine interpolation method to calculate the fraction of each day above the threshold temperature (D'Agostino and Schlenker 2016). To calculate total heating degree days, I sum up the total excess temperature over the period under consideration. Finally, I calculate district-level HDD using inverse square distance weighting from the district centroid.

I calculate HDD for various thresholds and seasons. Colmer (2021) shows that crops differ in their optimal HDD threshold values; I assign the threshold for individual crop yields based on their calculations. A single threshold is necessary for aggregate crop yields; I choose 25 C as the main threshold and conduct robustness for other thresholds. The main growing season months for most of India are the main monsoon ("Kharif") season of June-October, and I consider those months in the main HDD calculation.[8]

4.3.2 Rainfall shocks

To capture the effect of precipitation on aggregate crop yields, I follow Jayachandran (2006) and Kaur (2019) in constructing a piecewise function of rainfall. First, I calculate total precipitation in the planting and growing seasons for each district-year using daily rainfall data from TerraClimate provided by the Climatology lab.[9] Next, I calculate the twentieth and eightieth percentiles of each district's historical precipitation record. Then I designate rainfall extremes by creating high and low rainfall indicators as follows. The high rainfall dummy (*high_rain*) turns on if precipitation is above the eightieth percentile for the district, and zero otherwise; similarly the low rainfall dummy (*low_rain*) turns on if precipitation is lower than the twentieth percentile of historical precipitation, and zero otherwise. This nonlinear function has been extensively used to capture the effect of rainfall shocks on agricultural productivity, especially in India and allows us to flexibly capture the effect of excess and deficient rainfall on aggregate crop yields.

4.4 Further district controls

I construct district level controls from the Indian National Census 2001: fraction population that is SC/ST (caste groups that have historically been discriminated against), population density, literacy rate, male and female labor force participation ratio, fraction of labor force in agriculture, irrigated

[8] Kharif season Crops in some districts follow a different calendar, whereas Winter ("Rabi") season runs from roughly November to March. However, Colmer shows that monsoon season rainfall and temperature are important even for Rabi crops, since the amount of moisture retained in the soil through to the Rabi season depends on temperatures in the monsoon season. I do robustness around the season considered for the weather variables in the appendix

[9] https://www.climatologylab.org/terraclimate.html

cultivable land per capita and non-irrigated cultivable land per capita. I also use the NSS and crop data to create controls for baseline agricultural wages and agricultural productivity per worker.

4.5 NREGS data

The NREGS program was rolled out over a period of three years across the whole of India, as detailed previously. This information is available on the website of the ministry of rural development.[10] I use three district-level NREGS take-up measures: the number of NREGS person-days worked, the number of households working the maximum number of days permitted, and, NREGS labor expenditure. The NREGS data corresponds to the fiscal year (April 1 to March 31) and is available for 2006–2012. Administrative reforms in 2008 reduced large-scale corruption issues from inflated reporting in the official NREGS reports relative to survey data (Imbert and Papp 2015).

The provision of NREGS also fell dramatically in 2014 with the election of a new central government which was opposed to the program. Therefore, I limit the analysis to the agricultural year 2013-14.

4.6 Indian district administrative boundaries

In order to calculate weather data at the district level, I make use of publicly available district administrative boundaries in the form of shapefiles from the 2011 census[11].

4.7 Construction of district panel

There were 593 districts in the 2001 Indian census. Many district administrative boundaries changed over the 2001-2011 period, due to creation of new states or to provide better administrative efficiency through smaller districts. In order to construct a panel of districts over the 2001-2007 period, I began with a list of unchanged census districts from 2001 and 2011[12]. This master list is then sequentially matched with the NSS districts, crop data districts, the administrative boundary districts and the NREGS districts.

At the end of this process, I am left with 466 districts that form a panel from 2003-2013. I start the empirical analysis in 2003 because I use data from 1990-2002 to construct data on the variables

[10] Can be found at https://NREGS.nic.in/MNREGS_Dist.pdf
[11] I make use of the shapefiles provided by the Datameet google group
[12] Available at http://censusindia.gov.in/2011census/maps/administrative_maps/Final%20Atlas%20India%202011.pdf

used to construct the NREGS backwardness index is not available for districts in the panel before this year. I end the analysis in 2013 since the new government drastically reduced provision of NREGS after taking office in 2014, in keeping with their electoral promises.

Table 1 provides summary statistics for the baseline covariates used to assign NREGS districts, the main outcome and explanatory variables as well as controls. The table disaggregates this information by the three NREGS phases.

5 Research Design

5.1 Effect of weather shocks on crop yields

Weather shocks are an important predictor of crop yields in the literature. I document the importance of these weather shocks for individual crops in this section. I run the following regressions.

$$Weather_{dy} = \{HDD_{dy}, low\_rain_{dy}, high\_rain_{dy}\}$$

$$crop\_yield_{dy} = \tilde{\delta}\, Weather_{dy} + D_d + Y_y + \epsilon_{dy} \tag{1}$$

The vector $\tilde{\delta}$ denotes the effect of weather shocks on crop yields. The coefficient δ^{hdd} on HDD captures the average effect of an extra degree-day over historical levels on crop yields. Similarly, the coefficient on low_rain ($high\_rain$) captures the average effect of a low rainfall shock on crop yields. I use the data from 1990-2013, including pre-program years to maximize power. The HDD thresholds and growing seasons are taken from Colmer (2021), who choose these by maximizing R-squared from various regressions with different seasons and HDD thresholds. In the rest of the paper, for aggregate crop yields, the HDD threshold is 25 and the growing season is June-October.

Identification relies on the exogeneity of weather shocks controlling for district and year fixed effects (D_d and Y_y respectively). This assumption is quite common in the literature and does not raise any concerns in this setting either, given that yearly weather shocks are as good as randomly assigned. The main concern with inference is the spatial correlation in these shocks; I calculate Conley standard errors that account for this spatial correlation and also for autocorrelation across an arbitrary number of time periods using R routines provided by Thiemo Fetzer.[13] This approach toward inference is continued in the rest of the paper.

5.2 Effect of weather shocks on NREGS provision

Before conducting the main analysis, I test whether the provision of NREGS responds to adverse weather shocks. Evidence from studies such as Dutta et al. (2012) points to large demand for public works not always being met due to rationing. In this sense, administrative data on the quantum of money spent on labor, person-days worked or number of households that worked over 100 days are a result both of the demand for public works but also supply constraints by bureaucrats.

Therefore administrative data do not allow us to parse out whether labor demand on NREGS is higher during adverse weather shocks; rather, they allow us to test whether these measures - which depends on both demand and supply for public works - respond to adverse weather shocks. Given the corruption issues in the early years of NREGS implementation that were corrected by administrative reforms in 2008, I restrict these regression to 2009–2013, since these data come from the administrative system.

$$NREGS\_admin\_measure_{dy} = \tilde{\kappa}\, Weather_{dy} + D_d + Y_y + \epsilon_{dy} \tag{2}$$

The vector $\tilde{\kappa}$ denotes the effect of weather shocks on NREGS provision measures. Identification relies on the exogeneity of weather shocks controlling for district and year fixed effects (D_d and Y_y respectively). This assumption is quite common in the literature and does not raise any concerns in this setting either, given that yearly weather shocks are as good as randomly assigned. The main concern with inference again is the spatial correlation in these shocks which I tackle with the same approach described in previous section.

[13] See http://www.trfetzer.com/using-r-to-estimate-spatial-hac-errors-per-conley/

5.3 Effect of NREGS on weather sensitivity of crop yields

Equation 3 presents the regressions I run to test for increased weather sensitivity post NREGS. The outcome variable is the Revenue Value of Yield, the main measure of aggregate yields.[14]. The coefficients of interest is $\tilde{\beta_1} = \{\beta_1^{hdd}, \beta_1^{lrain}, \beta_1^{hrain}\}$; if these are different from zero then the sensitivity of aggregate yields to weather shocks is different post-program relative to pre-program sensitivities $\tilde{\gamma_1} = \{\gamma_1^{hdd}, \gamma_1^{lrain}, \gamma_1^{hrain}\}$. Identification of $\tilde{\beta_1}$ (and $\tilde{\gamma_1}$) relies on the exogeneity of yearly weather shocks. I use data from 2003-2013 since data from before 2003 are utilized to estimate the main measure of risk (area-weighted SD of the pre-program revenue value of yield).

The main threat to identification for $\tilde{\beta_1}$ is that another variable modulates the effect of weather shocks on crop yields at the same time as the program rolls out. In particular, differential time trends across the poorest districts which were targeted first by the program could be an issue. In order to alleviate such concerns, I run various specifications that account for this potential issues; equation 3 presents the most saturated specification using fixed effects.

In the first specification, I include the NREGS program dummy, weather variables as well as interactions of the three weather variables with the NREGS dummy. In the second specification, I allow a linear time trend interacted with a phase dummy. This controls for differential time trends in the outcome that differ by NREGS phase. In the third specification, I allow for these time trends to differ for each district based on initial values of observable characteristics that were used in the allocation of districts to NREGS phase. Fourthly, I interact weather shocks with values of these initial values of these characteristics to allow them to mediate the effect of weather shocks separately for each district.

$$\begin{gathered} log(RVY_{dy}) = \alpha_1 \, NREGS_{dy} + \tilde{\gamma_1} \, Weather_{dy} + \tilde{\beta_1} \, NREGS_{dy} * Weather_{dy} + \\ \lambda_d^p * t + \phi_1^1 \, Z_d * t + \phi_1^2 \, Weather_{dy} * Z_d + D_d + Y_y + \epsilon_{dy} \end{gathered} \tag{3}$$

[14] I also plan to present a measure that does away with price data

RVY is the revenue value of yield, $NREGS$ is the program dummy, $Weather$ is a vector containing $\{HDD$, low_rain and $high\_rain\}$, Z_d is a vector containing pre-program values of the variables entering the "backwardness" index, λ_d^p denotes the NREGS phase the district was part of, and D_d and Y_y are district and year fixed effects respectively.

While controlling for trends in these specifications allows us to build more confidence in the results, I also report results using first differences. First differences (FD) can make non-stationary data stationary and be more robust than fixed effects (FE) when data have strong autocorrelation, as can be seen in panel (a) of figure 1. Further, an FD specification that also includes a fixed effect allows for a district-specific linear growth rate g_d in the outcome. The FD approach is commonly used in the macroeconomic literature to deal with serial correlation in aggregated GDP data, similar to the measures I use in this paper. Equation 4 specifies the regression framework for the FD model.

$$\begin{aligned}\Delta log(RVY_{dy}) = \alpha_1\, \Delta NREGS_{dy} + \tilde{\gamma_1}\, \Delta Weather_{dy} + \\ \tilde{\beta_1}\, \Delta(NREGS_{dy} * Weather_{dy}) + g_d + \Delta Y_y + \Delta\epsilon_{dy}\end{aligned} \tag{4}$$

In both the panel and FD specifications, the coefficient α_1 captures the average effect of NREGS on revenue value of yield during normal weather years. A large NREGS literature uses similar difference-in-differences design with twoway fixed effects (TWFE) for district and year to estimate average effects on various outcomes (Imbert and Papp 2015; Berg et al. 2018; Gehrke 2019; Sheahan et al. 2020).[15]

Identification of the average effect of NREGS (α_1) requires that, conditional on the full set of controls, changes in the outcome post-treatment must be due to the program, on average, and not

[15] A literature on the bias of TWFE has developed recently, including that arising from differential timing. Callaway and Sant'Anna (2021) provide a framework to eliminate some of the bias arising from differential timing. Their approach relies on parallel trends conditional on baseline covariates, similar to this setting. But it is unable to test for increased weather sensitivity of aggregate crop yields after NREGS since there are no never-treated units in this setting. Therefore, I cannot conduct the whole analysis using their approach as it would limit the analysis to years until 2007, the year before the last phase of the program was implemented (since the CS estimator only makes use of untreated units as counterfactuals). Another complication in this setting is that treatment effect might evolve over time. Nevertheless, I plan to utilize their R *did* package to explore whether conditional parallel trends are likely to hold through a pre-trend check with data until 2007.

to another omitted variable. But (α_1) is not the main quantity of interest here; I also note that for the FD specification it is identified using just one period.

5.4 Effect of NREGS on risk index of crop choice

First, I verify that the three measures of risk in district crop mix have skill in predicting aggregate crop yields. If these measures are correlated with actual aggregate risk, higher values of RICC should lead to yield losses after a bad rainfall shock while increasing yields after a good rainfall shock. I test this idea in equation 5. I expect $\theta_1 > 0$ since higher risk with normal weather years should be correlated with higher returns, $\theta_2 < 0$ and $\theta_3 < 0$ since higher risk with bad rainfall shocks or higher than normal temperatures should reduce yields, and $\theta_4 > 0$ since higher risk with good rainfall should increase yields.

$$\begin{aligned} log(RVY_{dy}) = \theta_1\, log(RICC)_{dy} + \theta_2\, log(RICC)_{dy} * HDD_{dy} \\ + \theta_3\, log(RICC)_{dy} * Low\_Rain_{dy} + \theta_4\, log(RICC)_{dy} * High\_Rain_{dy} \\ + D_d + Y_y + \epsilon_{dy} \end{aligned} \tag{5}$$

Next, I test whether increased weather sensitivity of crop yields after NREGS can be explained by increased agricultural risk embedded in the district crop mix, using the three measures of Risk Index of Crop Choice (RICC) separately. Since this paper is interested in understanding crop choice as a driver of yield volatility, I focus on the RICC-SD that is constructed using the second moment of the pre-program distribution. The RICC-mean and RICC-SD measures are strongly correlated, reflecting the fact that higher revenue crops also have higher volatility. Changes in RICC come from changes in area weights across crops. Equation 6 below presents the regression specification.

$$\begin{aligned} log(RICC_{dy}) = \alpha_2\, NREGS_{dy} + \tilde{\gamma_2}\, Weather_{dy} + \tilde{\beta_2}\, NREGS_{dy} * Weather_{dy} + \\ \lambda_d^p * t + \phi_2^1\, Z_d * t + \phi_2^2\, Weather_{dy} * Z_d + D_d + Y_y + \epsilon_{dy} \end{aligned} \tag{6}$$

The literature on farmer investment decisions shows that they pay close attention to signals of what the weather is likely to be, including weather forecasts, before making investment decisions (Rosenzweig and Udry 2014). The Indian subcontinent receives most of its rainfall in the monsoon season that runs from June-September. One of the most important signals that farmers look at is early season rainfall; this is the period in which sowing/planting of most major crops takes place, and weather in the rest of the season affects crop growth but not crop choice. However, rainfall and temperatures in the monsoon season affect soil moisture for the Rabi (winter) season crops. Therefore, I control for planting season (June-July) weather in contrast to the whole monsoon season used in the yield regressions.

Since crop choice is baked in before full weather realization, the main coefficient of interest is α_2, the average effect of NREGS on aggregate risk in crop choice with a normal *planting* season weather. The coefficients $\tilde{\beta_2}$ and $\tilde{\gamma_2}$ are informative of any changes in crop choice that occur as a result of planting season weather that is a signal for the full weather realization; these coefficients are to be interpreted differently from $\tilde{\beta_2}$ and $\tilde{\gamma_2}$. As with the regressions in the previous section, I successively introduce trends that vary by phase and initial district characteristics, and interact weather with initial characteristics. I do not conduct a first difference analysis as for Revenue Value of Yield; the FD specification may not be as informative about α_2 since the first difference of the NREGS dummy turns on only once when the program starts.

5.5 Effect of NREGS on agricultural wages

In order to shed light on the labor market channel that could cause aggregate yields to become more sensitive to NREGS, I run the following regression.

$$\begin{aligned} log(wage)_{idy} &= \alpha_3 * NREGS_{dy} + \tilde{\gamma_3}\, Weather_{dy} + \tilde{\beta_3} NREGS * Weather_{dy} \\ &+ \quad \eta H_{idy} + \lambda_d^p * t + \phi_3^1\, Z_d * t + \phi_3^2\, Weather_{dy} * Z_d \\ &+ M_m + D_d + Y_y + \epsilon_{idy} \end{aligned} \tag{7}$$

The coefficient α_3 captures the average effect of NREGS on agricultural wages, while β_3 captures changes in the wage sensitivity to weather shocks post-NREGS. Since the early NREGS districts were selected partially based on district characteristics that could be correlated with the individual-level outcome, I utilize a similar strategy to the regressions for the revenue value and risk index by flexibly controlling for trends in baseline values and weather as well as allowing NREGS phase-wise trends. Identification of α_3 and β_3 requires similar assumptions to that for the Revenue Value of Yield regressions.

Since these are individual-level regressions I also include a month-of-year dummy that controls for any seasonal variation in wages. The vector H_{idy} contain the usual controls for gender, age group, education levels, caste, religion and marital status that are included in a Mincer-type regression.

Imbert and Papp (2015) utilized data from 2004 and 2007 to conduct a standard difference-in-difference analysis of the effect of NREGS on wages for casual labor. I extend their analysis by estimating this effect using employment and wage data from 2003, 2004, 2005, 2007, 2009 and 2011.

6 Results

6.1 Initial results

I start with the impact of weather shocks on crop yields in Table 2. I confirm results found in the literature showing that HDD and rainfall shocks are important determinants of agricultural productivity. In particular, an extra heating degree day in the growing season reduces aggregate revenue value of yield by 1.9%, a low rainfall shock reduces yield by 7.5% and a high rainfall shock increases yields by 4.3%.

Next, I discuss the effect of weather shocks on measures of NREGS program activity, as proxied by three different variables. These results are shown in table 3. We see that a low rainfall shock increases the number of per capita person-days by 0.303 SD, the per capita number of households that work more than 100 days by 0.321 SD and the per capita expenditure on labor by 0.482 SD, although the first result is not statistically significant.[16] On the other hand, a high rainfall shock reduces these measures by 0.2 SD, 0.014 SD and 0.110 SD respectively (the second measure is not statistically significant).

However, the effect of HDD shocks is not to increase program activity, but rather to *decrease* activity by 0.211 SD, 0.042 SD (insignificant) and 0.093 SD (only significant at 10% level). The rainfall results confirm that negative (positive) agricultural productivity shocks lower (increase) average earnings and therefore increase (decrease) demand for NREGS. The HDD results suggest that bureaucrats pay more attention to proxies of agricultural productivity rather than knowledge of true productivity, since rainfall shocks may be easier to measure and understand than temperature deviations.

6.2 Main results

Table 4 presents the results for increased weather sensitivity of aggregate crop yields after NREGS. The main coefficients of interest are for the interaction of NREGS and weather variables. This table shows that a low rainfall shock after NREGS reduces yield further by 8.1% in the most demanding specification in column 4, and 10.4% in the first difference in column 5. Reassuringly, this result is consistent across all specifications. In contrast, high rainfall shocks do not change the sensitivity of yield, while NREGS also does not change the effect of heating degree days, even though the first difference specification suggests a decrease in the sensitivity to HDD.

Appendix table A.8 conducts an indirect test of the parallel trends assumption by using a placebo treatment. I move the NREGS indicator up by 5 years, as if the program had first started in 2001 and not 2006. I estimate equation 3 on this data from 1998-2008. The coefficient on the *Low Rain X NREGS* variable is statistically indistinguishable from zero, providing reassuring evidence that the results from Table 4 are attributable to NREGS and not to omitted variables.

[16] Results are robust to an IHS transform of the provision measures (to allow for zeros) rather than a standardization.

Table 5 provides further evidence that the increased rainfall sensitivity is due to NREGS by adding an interaction term between weather, NREGS indicator and the lagged provision of NREGS to results in Table 4. I include all three measures of NREGS provision separately in different regressions using the most demanding specification of column 4 in Table 4. While I interpret the coefficients on *Low Rain X NREGS* as being causal, there may be need for caution in interpreting the coefficient on the lagged interaction term *Low Rain X NREGS Provision* in a causal manner. From Table 3, a negative rainfall shock increases provision on average; if this shock also affects agricultural productivity in the next year this correlation would be picked up in the interaction term. However, Kaur (2019) does not find a dependence of agricultural productivity on lagged rainfall shocks in the Indian context. I plan to test this with my data as well.

Going back to table 5, the estimate of the impact of a low rainfall shock post-NREGS on crop yield, conditional on average level of NREGS provision within district in the previous year, is between -5.3% and -9.9% in columns 1-6, and mostly measured precisely. The coefficients on *Low Rain X NREGS Provision* (*High Rain X NREGS Provision*) are estimates of the additional low (high) rainfall sensitivity from a 1 SD increase in NREGS provision in the previous year. The additional low rainfall sensitivity from 1 SD higher lagged provision ranges from -1.8 % to -8.4 %, measured quite precisely.[17] Additional high rainfall sensitivity is small and insignificant for two columns but precisely measured from 0.023% to 0.03% in four other columns.

These results indicate that the decision to provide NREGS after a negative rainfall shock has repercussions into the next year. First, there is a trade-off between its consumption smoothing benefits after a negative rainfall shock and the negative effect this provision may have on agricultural yields if there is another negative shock in the next year. On the other hand, conditional on a positive rainfall shock in the next year, there is a positive complementarity between between higher provision in a given year and next year's crop yields.

[17] Results are robust to an IHS transform of the provision measures (to allow for zeros) rather than a standardization.

6.3 Mechanisms

I now turn to the potential mechanism of risk in crop choice that has been hypothesized to explain increased weather sensitivity. Figure 2 shows that crops with higher mean revenue in a region are also likely to be subject to higher revenue volatility. Table 6 presents the results of a formal test, based on 5, of whether the constructed Risk Indices of Crop Choice capture real-work agricultural risk in the form of crop revenue volatility. The coefficients on *RICC* in column 1 and 2 for both RICC-Mean and RICC-SD show that higher risk is strongly correlated with higher returns in normal rainfall years, with elasticities of 1.17 and 1.073 respectively.

On the other hand, coefficient on *RICC* for column 3 suggest RICC-Skew does not predict returns during average years. Coefficients on the interaction term *RICC X HDD* are negative as expected for all three measures and strongly significant for RICC-Mean and RICC-SD, with small elasticities of -0.003. Tellingly, given the importance of rainfall shocks in the Indian agricultural context, the coefficients on *RICC X Low Rain* show a consistent pattern of reductions in crop revenue, with elasticities for RICC-Mean and RICC-SD of -0.005. The coefficient on RICC-Skew should not be interpreted as an elasticity since the IHS transform behaves like a log transform only with values above 10 or so for the raw variable (Bellemare and Wichman 2020).[18] But the coefficient is in the same direction as the other two. Similarly, the coefficients on *RICC X High Rain* are positive and significant for all three measures of aggregate risk. Now that we have seen that these measures of aggregate risk have skill in predicting crop revenue, we should be able to tease out whether NREGS shifts district crop mix toward higher risk, higher revenue crops that are also positively skewed. Table 7 tests these hypotheses.

The three columns of table 7 are estimated for each of the three measures of risk in crop choice using the most demanding specification from equation 6 including phase-wise time trends, baseline controls interacted with time trends and weather shocks interacted with baseline controls. The coefficient on $NREGS$ is of interest and estimates the average impact on each measure of risk

[18] The max skewness in the data is 3.33

in crop choice during normal planting season years. From columns 1 and 3, there do not seem to be any changes in the average district crop mix toward higher mean yield crops (col 1), or more positively skewed crops (col 3). The coefficient in column 2 is significant at the 10% level and suggests a shift in average district crop mix toward more volatile crops. This result suggests that NREGS may have increased average risk in crop choice during normal planting seasons by 0.08%, as measured by the RICC-SD. Such a result could explain part of the increased sensitivity of yields to a negative rainfall realization.

However, there are a couple of reasons this result may not explain the increased sensitivity. The elasticity of Revenue Value of Yield to RICC-SD in Table 6 column 2, row 3 is -0.007%. Therefore, an increase in risk of 0.08% can only explain a (0.08*0.007) = 0.0056% reduction in yield. The actual reduction in yield with a low rainfall shock after NREGS is abut 10%.

Secondly, in table A.9, I test whether the results in table 7 satisfy the indirect parallel trends assumption. Column 2 of table A.9 shows that the placebo program dummy increases RICC-SD by 1.3%. Since the program was not in place at this time, the parallel trends assumption seems to be violated in this case, and a pre-existing trend may be driving the result observed in table 7. So, the true effect of NREGS on the Risk Index of Crop Choice may be even smaller, and it is unlikely that this particular mechanism is the cause of the increased rainfall sensitivity of crop yields after NREGS.

Finally, I provide some evidence in favor of the labor market channel. The NREGS literature documents clear increases in wages for unskilled labor, mainly due to general equilibrium effects that reallocate workers away from the private market (Muralidharan, Niehaus, and Sukhtankar 2016; Sukhtankar 2017). But beyond this level effect on unskilled wages, the coefficient on *Low Rain X NREGS* in table A.10 demonstrates that NREGS also reduces wage sensitivity to low rainfall shocks (Santangelo 2019). This mechanism can increase labor costs for farmers who are already dealing with a negative productivity shocks, thereby exacerbating the net productivity losses.

7 Conclusion

The stated purpose of NREGS was to improve livelihood security of the rural poor by providing them with income from manual work on demand. The program succeeded in its main goal of improving earnings for the poor and helped reduce poverty (Sukhtankar 2017). But I document that the program has economically large implications for the volatility of agricultural output by making aggregate yields more sensitive to negative rainfall shocks. I construct novel measures of aggregate risk in district crop mix to analyze whether the increased sensitivity is due to higher risk-taking by some farmers in response to the social insurance properties of NREGS. I show that these measures are meaningful because they have skill in predicting the volatility of yields. Using these measures of risk, I argue that the increased crop sensitivity cannot be explained by higher aggregate risk in the district crop mix. It is important to note that these measures of risk in crop choice may not capture other agricultural risk such as increased use of costly inputs such as fertilizers or machinery that could also reduce yields during a bad year if farmers are also credit constrained at the same time. Further research is necessary to understand those mechanisms better.

I also provide evidence consistent with the literature on the labor market channel that NREGS makes agricultural wages less elastic to rainfall shocks. This inhibits any pro-cyclical correction that would reduce labor costs during harvest and thereby prevent additional crop losses. However, the welfare implications of this are not straightforward; small and medium farmers who are net sellers of labor on the agricultural market indirectly benefit through higher earnings from the wage effect as well as directly through provision of NREGS, transferring agricultural risk to larger farmers. In a utilitarian sense, this might be a net welfare gain since the marginal utility of consumption of smaller farm-households is higher than that of larger ones, and they are also more numerous. There also exist positive (negative) complementatarities at the intensive margin of higher provision of NREGS to deal with rainfall shock in a given year, and subsequent aggregate yield if a positive (negative) rainfall shock is realized next year.

The aggregate food security implications of workfare programs, especially in the context of climate change, are not very well-understood. This paper sheds some light on this question for India, pointing to the labor market channel as the most important channel. By transferring yield risk from smaller to larger farmers while simultaneously increasing incomes of the latter, NREGS improves consumption smoothing for the poorest. But larger weather shocks in the future might lead to much larger yield losses and aggregate food security concerns, especially if the ability to store or source essential food grains and other staples is low. The literature on the implications of climate change for agriculture discusses trade across regions with less-correlated changes in climate as a potential solution (Costinot, Donaldson, and Smith 2016). However, shocks are likely more correlated within-country. Another avenue would be structural transformation such that fewer people depend on agriculture for livelihoods, and only the most productive farmers stay in agriculture (Suri 2011). If these farmers are able to consolidate land, they may be even more productive, given that larger farmers are less credit constrained and more able to invest in technologies (Foster and Rosenzweig 2017). But, land market consolidation is difficult given land market frictions, and other barriers to structural transformation generally, which could also make increased rainfall sensitivity of yields from NREGS more salient.

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9 Figures and Tables

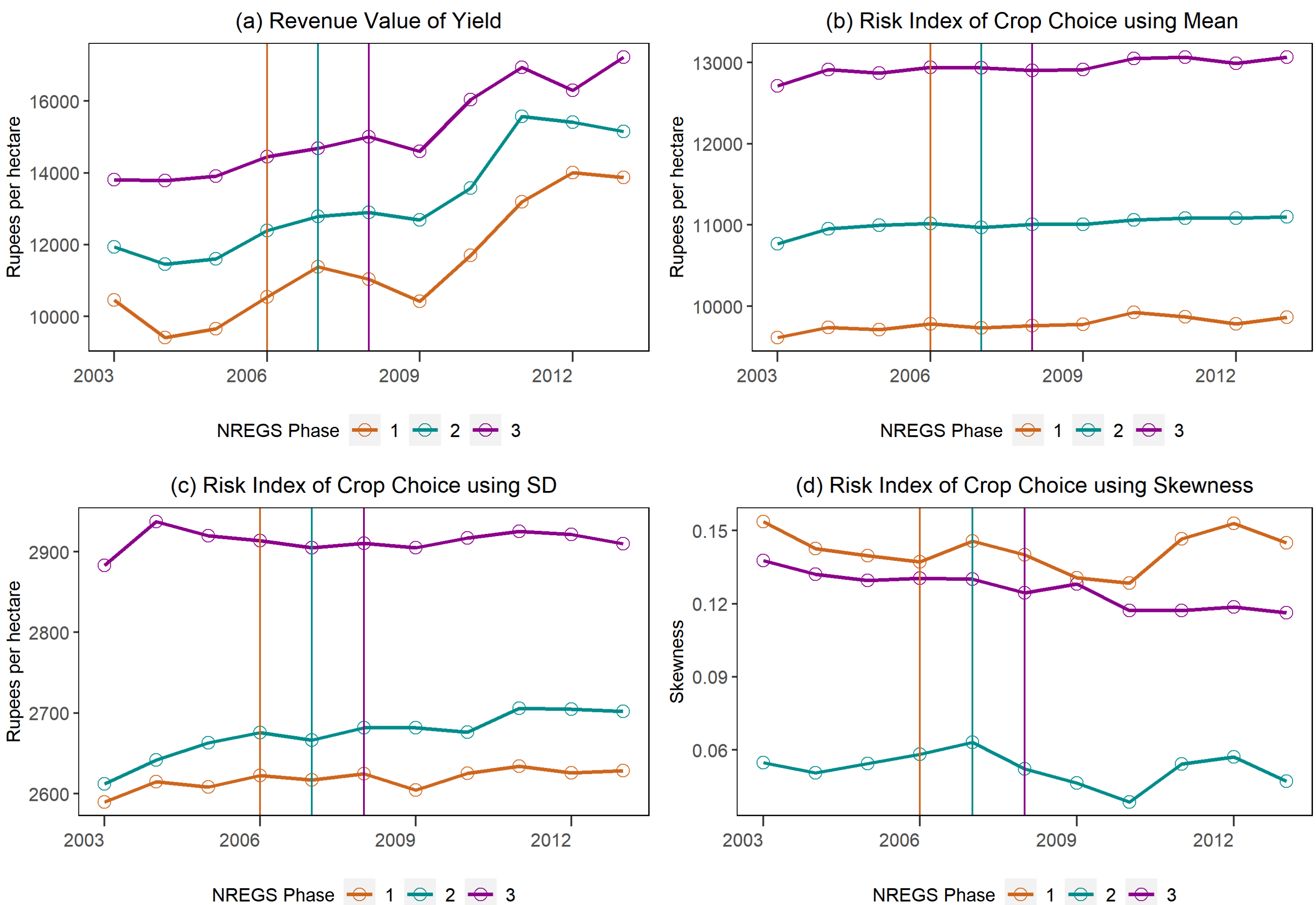

Figure 1: Trends in Revenue Value of Yield and Risk Indices of Crop Choice. The first three moments for the distribution of revenue value of yield are separately calculated for each of the 16 crops in each of the 96 regions using data on yearly revenue value of yield between 1990-2002. The Risk Index of Crop Choice for each moment is the calculated by yearly crop area-weighted average of the specified moment of this distribution for the region within which the district falls (5.5 districts within each region on average). Panels (b), (c) and (d) display the yearly average of these risk indices, separately for each NREGS phase. Vertical lines provide NREGS start year by phase. ↩

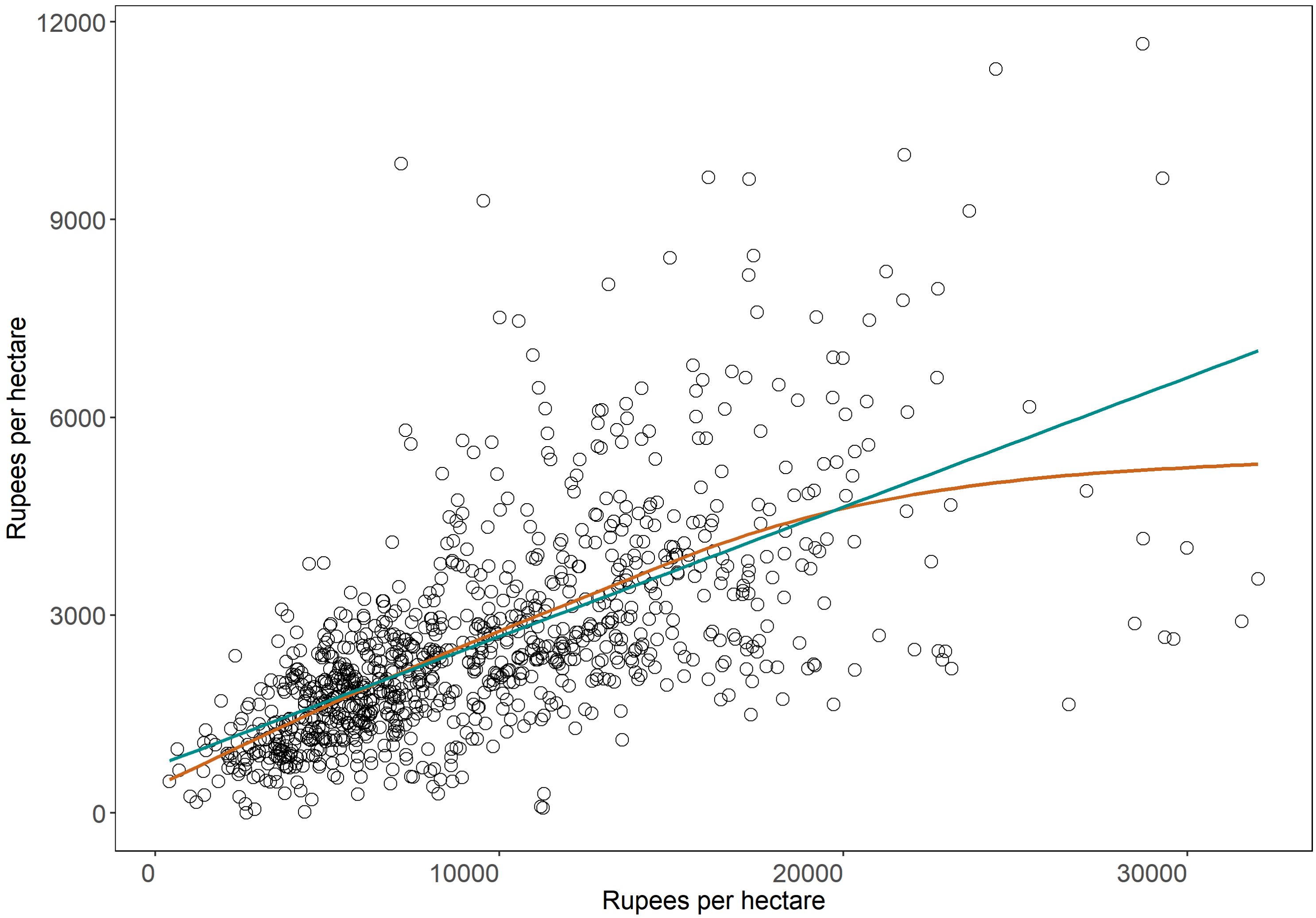

Figure 2: Mean (y-axis) vs SD (x-axis) of pre-2003 revenue value of yield distribution. Each dot represents a crop-region. The Mean and SD for this distribution are calculated for each of the 16 crops in each of the 96 regions separately using data on yearly revenue value of yield between 1990-2002. Linear and cubic fits are also shown within the figure. ↩

Table 1: Summary Statistics

Variable	Early - 2006 N	Early - 2006 Mean	Early - 2006 SD	Mid - 2007 N	Mid - 2007 Mean	Mid - 2007 SD	Late - 2008 N	Late - 2008 Mean	Late - 2008 SD
Panel A: Pre-program variables used to determine district NREGS phase									
Share of lower castes	169	0.35	0.17	98	0.25	0.1	200	0.2	0.1
Ag product per capita (Rs/person)	169	5563	5930	98	7053	8731	200	12196	13910
Casual daily labor wage (Rs)	169	26.77	17.81	98	26.2	18.65	200	21.86	18.21
Panel D: NREGS Variables									
NREGA dummy	1859	0.73	0.45	1078	0.64	0.48	2210	0.55	0.5
HH worked > 100 days (Count/person)	1715	0.04	0.08	1015	0.02	0.05	2109	0.01	0.05
Person-days worked (Count/person)	1715	2.11	4.64	1015	1.74	3.95	2109	1.35	3.47
Labor Expenditure per capita (Rs/person)	1715	0.61	0.67	1015	0.42	0.54	2109	0.29	0.51
Panel B: Agricultural Outcomes									
Revenue value of yield (Rs/ha)	1859	11427	4427	1078	13226	4980	2210	15159	6306
RICC-Mean (Rs/ha)	1859	9778	3229	1078	11005	3503	2210	12941	4703
RICC-SD (Rs/ha)	1859	2618	790	1078	2674	815	2210	2913	1238
RICC-Skew (Skewness)	1859	-2.66	1.3	1078	-2.63	1.46	2210	-2.7	1.97
Panel C: Weather Variables - monsoon season (Jun-Oct)									
Demeaned HDD (Degree-days)	1859	0.33	0.59	1078	0.31	0.5	2189	0.45	0.91
Low Rain Dummy	1859	0.23	0.42	1078	0.25	0.43	2210	0.22	0.42
High Rain Dummy	1859	0.27	0.44	1078	0.27	0.44	2210	0.27	0.44
Panel D: Weather Variables - planting season (Jun-Jul)									
Demeaned HDD (Degree-days)	1859	-9.82	11.95	1078	-11.34	8.99	2189	-10.93	8.34

continued

Table 1: Summary Statistics (Continued)

Low Rain Dummy	1859	0.27	0.45	1078	0.27	0.44	2210	0.27	0.44
High Rain Dummy	1859	0.26	0.44	1078	0.24	0.43	2210	0.25	0.43
Panel E: Wage outcomes									
Ag daily labor wage (Rs)	53762	84.67	57.18	34689	94.69	78.94	53362	111.61	90.26

Notes: Time-invariant pre-program variables in Panel A are calculated from the National Sample Survey 2004 and Population Census of 2001. RICC in panel B refers to the Risk Index of Crop Choice. Yearly NREGS provision variables in Panel B are from 2009-2015. Weather variables in Panels C and D are calculated for from the Google Earth Engine. Individual wage outcomes in Panel E are the NSS. ↩

Table 2: Impact of weather shocks on aggregate and individual crop yields

	Dependent variable: log(RVY)					
	(1)	(2)	(3)	(4)	(5)	(6)
HDD	-0.019^{**}	-0.016^{*}	-0.027^{***}	-0.052^{***}	-0.132	-0.035^{*}
	(0.008)	(0.010)	(0.006)	(0.019)	(0.100)	(0.019)
Low Rain	-0.075^{***}	-0.073^{***}	-0.039^{***}	-0.023	-0.031	-0.128^{***}
	(0.016)	(0.023)	(0.013)	(0.016)	(0.036)	(0.025)
High Rain	0.043^{***}	0.055^{***}	0.043^{***}	0.026	0.035	-0.011
	(0.012)	(0.017)	(0.012)	(0.019)	(0.029)	(0.018)
Crop	Aggregate	Rice	Wheat	Sugarcane	Cotton	Groundnut
Observations	10,134	9,421	8,353	4,136	4,136	6,322
R2	0.787	0.780	0.829	0.545	0.544	0.570
District and Year FE	X	X	X	X	X	X

Notes: Estimation on data from 1990-2013. RVY refers to Revenue Value of Yield. Each column presents estimates for either the aggregate revenue value of yield for all crops weighted by area planted, or individual crop revenue value of yield. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

Table 3: NREGA provision in response to weather shocks

	Dependent variable: Standardized per capita provision		
	(1)	(2)	(3)
HDD	-0.211^{**}	-0.042	-0.093^{*}
	(0.083)	(0.064)	(0.050)
Low Rain	0.303	0.321^{***}	0.482^{***}
	(0.203)	(0.111)	(0.117)
High Rain	-0.205^{*}	-0.014	-0.110^{*}
	(0.113)	(0.078)	(0.060)
NREGS Provision var	Person days	Num HH > 100 Days	Labour Expenditure
Observations	2,117	2,117	2,117
R2	0.708	0.680	0.787
District and Year FE	X	X	X

Notes: Estimation on data from 2009-2013. Each column presents estimates for a standardized measure of per capita NREGS provison. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. All provision variables are converted to per capita and then standardized. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

Table 4: Impact of NREGA on Weather Sensitivity of Aggregate Yields

	Dependent variable: log(RVY)				
	(1)	(2)	(3)	(4)	(5)
NREGA	−0.003	0.013	0.018	0.016	0.042
	(0.028)	(0.030)	(0.030)	(0.029)	(0.026)
HDD X NREGA	0.023	0.027	0.021	0.023	0.043^{**}
	(0.017)	(0.017)	(0.016)	(0.016)	(0.021)
Low Rain X NREGA	-0.081^{**}	-0.081^{**}	-0.085^{**}	-0.081^{**}	-0.104^{***}
	(0.040)	(0.040)	(0.039)	(0.037)	(0.035)
High Rain X NREGA	0.007	0.012	0.005	0.006	−0.020
	(0.027)	(0.027)	(0.027)	(0.028)	(0.032)
Observations	5,132	5,132	5,126	5,126	4,665
R2	0.810	0.811	0.813	0.815	0.086
Trend X Phase		X	X	X	
Trend X Controls			X	X	
Weather X Controls				X	
First Difference					X
District and Year FE	X	X	X	X	X

Notes: Years 2003-2013. RVY refers to aggregate Revenue Value of Yield for all crops weighted by area planted. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

Table 5: Impact of Provision on Weather Sensitivity of Aggregate Yields

	Dependent variable: log(RVY)					
	(1)	(2)	(3)	(4)	(5)	(6)
NREGA	0.019	0.009	0.012	0.058**	0.045*	0.057**
	(0.029)	(0.029)	(0.030)	(0.026)	(0.025)	(0.027)
Provision	−0.019*	0.011	−0.018	0.010	−0.021	0.023
	(0.011)	(0.011)	(0.013)	(0.009)	(0.019)	(0.020)
HDD X NREGA	0.018	0.024	0.022	0.012	0.021	0.018
	(0.015)	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)
Low Rain X NREGA	−0.072*	−0.080**	−0.053	−0.085**	−0.099***	−0.070*
	(0.037)	(0.037)	(0.040)	(0.039)	(0.038)	(0.041)
High Rain X NREGA	−0.005	0.007	−0.009	−0.047	−0.034	−0.052*
	(0.029)	(0.029)	(0.029)	(0.031)	(0.031)	(0.031)
HDD X Provision	0.013*	0.006	0.005	0.009**	0.012	0.004
	(0.007)	(0.005)	(0.005)	(0.004)	(0.008)	(0.008)
Low Rain X Provision	−0.018*	−0.056***	−0.040**	−0.021**	−0.084***	−0.043**
	(0.009)	(0.022)	(0.020)	(0.010)	(0.030)	(0.019)
High Rain X Provision	0.030***	−0.004	0.023**	0.028***	0.006	0.027**
	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.012)
Provision Variable	HH100Days	PDays	LabExp	HH100Days	PDays	LabExp
Observations	4,872	4,872	4,872	3,945	3,945	3,945
R2	0.820	0.818	0.820	0.112	0.107	0.111
First Differences				X	X	X
District and Year FE	X	X	X	X	X	X

Notes: Years 2003-2013. RVY refers to aggregate Revenue Value of Yield for all crops weighted by area planted. Provision is the lagged value of the per capita standardized NREGA measure listed under each column. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. *p<0.1; **p<0.05; ***p<0.01. ↩

Table 6: Does Risk Index of Crop Choice predict Crop Yields?

	Dependent variable: log(RVY)		
	(1)	(2)	(3)
RICC	1.170***	1.073***	−0.109
	(0.160)	(0.149)	(0.108)
RICC X HDD	−0.003**	−0.003**	−0.025
	(0.001)	(0.001)	(0.021)
RICC X Low Rain	−0.005*	−0.007**	−0.120***
	(0.003)	(0.003)	(0.046)
RICC X High Rain	0.005***	0.006***	0.075**
	(0.002)	(0.002)	(0.035)
RICC Var	log(RICC-Mean)	log(RICC-SD)	ihs(RICC-Skew)
Observations	5,132	5,132	5,132
R2	0.825	0.818	0.806
District and Year FE	X	X	X

Notes: Years 2003-2013. RVY refers to aggregate Revenue Value of Yield for all crops weighted by area planted. RICC refers to the Risk Index of Crop Choice. Each column presents an estimate using a different RICC that is constructed by crop area-weighting one of the first three moments of the the pre-2003 crop revenue distribution. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon season (June-October)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

Table 7: Impact of NREGA on Risk Index of Crop Choice

	Dependent variable:		
	log(RICC-Mean)	log(RICC-SD)	ihs(RICC-Skew)
	(1)	(2)	(3)
NREGA	0.001	0.008*	0.002
	(0.005)	(0.004)	(0.006)
HDD X NREGA	0.001*	0.001**	0.0002
	(0.0003)	(0.0002)	(0.0002)
Low Rain X NREGA	0.0003	−0.006	−0.010*
	(0.006)	(0.004)	(0.006)
High Rain X NREGA	0.009	0.001	−0.005
	(0.008)	(0.006)	(0.006)
Observations	5,126	5,126	5,126
R2	0.982	0.985	0.982
District and Year FE	X	X	X

Notes: Years 2003-2013. RICC refers to the Risk Index of Crop Choice. Each column presents an estimate using a different RICC that is constructed by crop area-weighting one of the first three moments of the the pre-2003 crop revenue distribution. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **planting period (June-July)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

10 Appendix

Table A.8: Placebo Impact of NREGA on Weather Sensitivity of Agg. Yields

	Dependent variable: log(RVY)				
	(1)	(2)	(3)	(4)	(5)
NREGA	0.020	0.019	0.019	0.020	−0.028
	(0.027)	(0.026)	(0.026)	(0.024)	(0.031)
HDD X NREGA	0.014	0.013	0.011	0.013	0.003
	(0.021)	(0.022)	(0.021)	(0.020)	(0.032)
Low Rain X NREGA	−0.014	−0.014	−0.013	−0.008	0.033
	(0.039)	(0.039)	(0.039)	(0.037)	(0.035)
High Rain X NREGA	−0.043	−0.043	−0.041	−0.033	−0.029
	(0.041)	(0.042)	(0.043)	(0.043)	(0.042)
Observations	5,092	5,092	5,091	5,091	4,625
R2	0.816	0.816	0.816	0.818	0.157
Trend X Phase		X	X	X	
Trend X Controls			X	X	
Weather X Controls				X	
First Difference					X
District and Year FE	X	X	X	X	X

Notes: Years 1998-2008. RVY refers to aggregate Revenue Value of Yield for all crops weighted by area planted. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported.

Table A.9: Placebo Impact of NREGA on Risk Index

	Dependent variable:		
	log(RICC-Mean)	log(RICC-SD)	ihs(RICC-Skew)
	(1)	(2)	(3)
NREGA	0.011	0.013*	-0.006
	(0.007)	(0.007)	(0.006)
HDD X NREGA	0.0005*	0.0002	-0.0004
	(0.0002)	(0.0002)	(0.0003)
Low Rain X NREGA	-0.006	-0.009	0.001
	(0.006)	(0.006)	(0.005)
High Rain X NREGA	0.002	-0.00002	0.013**
	(0.007)	(0.006)	(0.005)
Observations	5,091	5,091	5,091
R2	0.983	0.984	0.981
District and Year FE	X	X	X

Notes: Years 1998-2008. RICC refers to the Risk Index of Crop Choice. Each column presents an estimate using a different RICC that is constructed by crop area-weighting one of the first three moments of the the pre-2003 crop revenue distribution. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **planting period (June-July)**. Conley standard errors using a cutoff of 1000 km and arbitrary autocorrelation up to 5 years are reported. All columns include district and year fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩

Table A.10: Impact of NREGA on wages for hired agricultural labor

	Dependent variable: log(Wage)			
	(1)	(2)	(3)	(4)
NREGA	0.017	0.008	0.012	0.012
	(0.027)	(0.027)	(0.027)	(0.027)
HDD X NREGA	−0.004	0.006	0.0002	−0.002
	(0.016)	(0.015)	(0.016)	(0.016)
Low Rain X NREGA	-0.056^{*}	-0.055^{*}	-0.053^{*}	-0.057^{**}
	(0.029)	(0.028)	(0.028)	(0.028)
High Rain X NREGA	−0.043	−0.037	−0.043	−0.044
	(0.028)	(0.028)	(0.027)	(0.027)
Observations	129,845	129,845	129,845	129,845
R2	0.387	0.387	0.388	0.389
Trend X Phase		X	X	X
Trend X Controls			X	X
Weather X Controls				X
District, Month and Year FE	X	X	X	X

Notes: Years 2003, 2004, 2005, 2007, 2009 and 2011. Outcome variable is log of individual daily wage earnt while working on manual labor tasks in the private market. HDD refers to heating degree days above 25C. Low and High Rain are dummies for rainfall below and above 20th or 80th percentile of historical rainfall. Weather variables are for the **monsoon period (June-October)**. Standard errors are clustered at the district level. All columns include district, year and month fixed effects. *p<0.1; **p<0.05; ***p<0.01. ↩