Have you ever seen the rain? Effect of Rainfall Shocks on Agricultural Wages in India

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October 2025

Abstract

This paper examines how rainfall shocks affect agricultural wages in India, arguing that farmers rely on recent experiences rather than long-run climate normals when forming expectations under uncertainty. Using a rolling three-year window instead of the conventional 30-year historical distribution to define rainfall shocks, the study analyzes TCI-ICRISAT district-level panel data (1993-2017) across 542 districts in 20 states. Results show that districts experiencing negative rainfall shocks during the sowing season combined with positive shocks during the harvest season experience wage reductions of 5.2% for male and 4.1% for female agricultural field laborers. These negative effects intensify in districts with larger rice cultivation areas and more irrigated land, suggesting irrigation infrastructure may inadvertently amplify labor market vulnerabilities during certain shock combinations. However, districts with greater market access experience moderated wage impacts. The paper complements the district-level analysis by using household-level data from the India Human Development Survey to highlight the underlying labor-leisure trade-off in labor supply decisions. The estimation follows a simultaneous equation modeling framework where the decision to supply labor and wages paid for hired labor are jointly determined within a three-stage least squares (3SLS) framework. Estimates from the household model suggest that income and substitution effects interact to shape labor supply responses and equilibrium wage outcomes in response to rainfall shocks.

Key words: Rainfall Shocks, Wages, Recency Bias, India
JEL Codes: Q12 Q54 J43 J22

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1 Introduction

Economic agents' decision-making processes under uncertainty deviate from the rational expectations framework (Kala, 2017). In the absence of complete information, making judgments under uncertainty involves the use of alternative learning mechanisms- or heuristics such as the availability heuristic, and reinforcement strategy (Tversky & Kahneman, 1974). The availability heuristic (recency bias) predicts that effects on expectations and decisions are larger for more recent experiences, while the reinforcement strategy suggests that the effects on expectations are cyclical. Although this might lead to systematic and predictable errors, Malmendier and Wachter (2024) finds empirical evidence of the long-lasting effects of personal past experiences in finance and economics. The Indian monsoon is a particularly relevant example of an environment that is characterized by uncertainty. The uncertainty is not only captured by the lack of access to forecasts (despite recent improvements), but also by the changes in the weather distribution itself. Over the second half of the 20th century, the rainy season in India has gradually shifted towards a pattern of reduced total precipitation and rare rainfall events, resulting in higher risk of both droughts and floods (Bowden et al., 2023). Anomalies in the rainfall patterns not only lead to economic losses due to floods or droughts, but they also result in crop failures and food supply disruptions. Through its impact on agricultural income, above or below 'normal' rainfall patterns play a significant role in determining the welfare of rural households (Blakeslee & Fishman, 2018; Dimitrova & Muttarak, 2020; Jacoby & Skoufias, 1998; Jensen, 2000; Rosenzweig & Stark, 1989; Rosenzweig & Wolpin, 1993; Shah & Steinberg, 2017).[1] With approximately 55 percent of India's net sown area dependent upon rainfall- particularly during the sowing season between May and June (Shagun, 2023)- farmers in India essentially operate in an environment that is risky, uncertain, and characterized by incomplete information. Farmers either use available forecasts or form their own expectations of rainfall patterns to make ex-ante cropping decisions. The presence of accurate rainfall forecasts benefits farmers by reducing the uncertainty and bias associated with heuristic-based decisions. Under complete information, following the Bayesian learning framework, farmers would form expectations using long-run climate normals, and recent shocks would not affect their posterior expectation and therefore ex-ante production decisions in subse-

[1]Earlier studies have also shown that households resort to a host of strategies to cope with weather-related shocks such as supply additional hours of labor (Kochar, 1999); reduce investment in human capital development of children (Jacoby & Skoufias, 1998; Jensen, 2000; Shah & Steinberg, 2017); marrying daughters to distant households (Rosenzweig & Stark, 1989); sell productive assets (Rosenzweig & Wolpin, 1993); borrow from microfinance institutions (Islam & Maitra, 2012); engage in non-farm activities with low risk (perhaps also low return) (Ito & Kurosaki, 2009); and re-allocate labor to public works program (Azam, 2011).

quent years any differently than shocks that were experienced further back in time.

This study revisits the question of how rainfall shocks influence agricultural wages. Earlier studies have investigated the question by defining rainfall shocks using deviations from long-run normals - typically the previous 30-year rainfall distribution (Jayachandran, 2006; Kaur, 2019; Mahajan, 2017; Maitra & Tagat, 2023). But such analysis is based on the assumption that farmers can access all the relevant information for the previous 30 years. While this might be true for climate scientists engaged in academic exercise, real-time decisions rest upon the crucial assumption that farmers can access this information through forecasts translated into local actionable information. However, there is a lack of access to real-time forecasts (Palit, 2025). In fact, Arora and Feng (2024) argue that approximately 70 % of farmers in the western frontier of the US corn belt misperceive past weather changes. If forecast limitations constrain farmers even in the US—where meteorological infrastructure and predictive accuracy far exceed those in Africa and Asia—the forecasting challenges facing farmers in the global South, including India, are substantially more severe. Despite recent improvements in rainfall prediction in India, information gaps and accessibility barriers likely persist in these regions. As a result, decision-making is guided by alternative heuristics. This challenges the earlier analysis of rainfall shocks on wages that relied on historical normals.

We propose an alternative definition of rainfall shock- one that espouses the principles of the availability heuristic. We argue that recent experiences have a relatively larger effect on the expectation formation mechanisms of farmers. This was theoretically and empirically demonstrated in Kala (2017). Comparing the learning mechanisms under the Bayesian framework with the alternative mechanisms, especially one where farmers attach greater weights to recent realizations (robust learning framework) Kala (2017) finds that the mean-squared error of the model that uses the robust learning framework to predict farmer behavior is lower than the other Bayesian models. Jayachandran (2006) and Kaur (2019) have defined positive (negative) rainfall shock if the rainfall in time-period t and district d is greater (less) than the 80th (20th) percentile of the long-run rainfall distribution in the district. We follow the same procedure but use a modified reference period to define the rainfall shock thresholds. Brey et al. (2022) identifies that the optimal lag-length of the effect of monsoon rainfall shocks on yield, wages, and food prices in India is 3 years (Brey et al., 2022). Against the backdrop of farmers' relying on alternative heuristics, we redefine the reference period used to define rainfall shocks as the 3-year moving period of previous rainfall realizations. Due to the rolling nature of the reference period, our definition of rainfall shock helps capture the relativity of shocks based on the available information. We provide some evidence of the presence of recency bias (refer to Appendix D).

Using this definition, the paper estimates the impact of rainfall shocks on male and female agricultural field labor wages. We initially estimate the impact of shocks using district-level data on wages. Rainfall shocks are defined for the sowing and harvest seasons to capture shocks over an entire agricultural year and also ensure temporal compatibility with the dependent variable. We use the Kharif season as the benchmark because it accounts for the majority of agricultural production and is highly dependent upon the monsoons. Our main analysis of a yearly district-level panel dataset employs a two-way fixed effects model. We find that a combination of negative shocks in the sowing season and positive shocks in the harvest season has the most salient impact on male and female field labor. Districts that experience this combination of shocks have 4.1 percent and 5.2 percent lower wages for female and male field labor compared to districts that experience normal rainfall. Thereafter, we investigate the sensitivity of this effect to various control variables- district-level rice acreage, area under irrigated rice, and source of irrigation. We also explore the role of primary agricultural markets in moderating the effect of shocks on wages. We find that the intensity of the negative effect of the negative sowing and positive harvest shock on wages increases with rice area and irrigated area. While irrigation infrastructure can act as a buffer during rainfall deficits, it can have an unintended consequence in the labor market by reducing wages for field labor. However, wages are higher for districts with more agricultural markets that also experience negative sowing and positive harvest shocks. Thus, highlighting the role that competition- captured by more markets in a district- can play in moderating the negative impact of rainfall shocks on wages.

We explore the potential mechanisms that can be driving these results by supplementing the district-level analysis with household-level data from the India Human Development Survey (IHDS) (Desai & Vanneman, 2015; Desai et al., 2008). We posit our analysis within the framework of an agricultural household model (Singh et al., 1986)- characterized by joint production and consumption decisions where family members optimize their time allocation between on-farm work, off-farm labor supply, and leisure, while simultaneously determining agricultural output levels and hired labor demand for their farming operations.[2] This integrated decision-making process fundamentally differs from pure consumer households or firms because agricultural households experience direct profit effects from price and productivity changes. The simultaneity arises because changes in agricultural productivity or rainfall patterns alter farm profits, which in turn affect household income and consumption patterns, while simultaneously modifying the marginal productivity of both family and hired labor, creating feedback effects between production decisions and labor market participation. Given that rainfall shocks

[2]refer to Appendix B for a detailed discussion of this model.

affect farm profitability, alter the marginal productivity of labor inputs, and modify household income through the profit effect, estimating the effect of weather variability requires a simultaneous equations approach that facilitates the joint determination of agricultural labor supply and hired wages in response to rainfall shocks. Using a three-stage least squares model (3SLS), we find that when faced with negative sowing and positive harvest season shocks, the initial income shock prompts households to seek out more wage labor (income effect). However, the labor demand does not recover due to excess rain in the harvest season, failing to absorb all the labor supplied. As a result, while the total change in labor supply is muted or insignificant, the persistence of an overabundance of willing workers relative to available jobs leads to a significant drop in local field labor wages, reflecting the dominance of the income effect. The results from our household-level analysis help explain the labor-leisure tradeoff that drives the relationship between rainfall shocks and field labor wages.

This paper contributes to the growing literature on adaptation to weather shocks. Although we challenge the existing practice of using long-run normals to model weather and climate shocks, we understand that it is the most appropriate scientific approach to addressing the issue. However, our key contribution is in providing an estimate of farmers' decision-making under uncertainty- which challenges the assumptions of the Bayesian learning framework. We update the existing literature on rainfall shocks and wages by, i) analyzing a more recent time frame (1993-2017); ii) supplementing district-level analysis with household-level data to identify the underlying mechanisms; and iii) highlight the potential role that increased access to markets and competition can play in ameliorating some of the negative impact of shocks on rural labor markets. The results from this paper can be interpreted as estimates of the decision-making process when farmers lack access to real-time, actionable rainfall forecasts. It makes a compelling case for scaling up the recent efforts to provide real-time information to farmers in an accessible format through digital media such as messages on their mobile phones (Greef, 2025). The findings from this study establish a baseline against which future research can compare the effects of real-time rainfall forecasts on farmers' decision-making processes.

The rest of the paper is structured as follows. The data and estimation strategy are discussed in sections 2 and 3. Results are analyzed in section 4, and section 5.1 discusses the underlying mechanisms. In section 6 we highlight the policy implications of the key results from this study. Finally, section 7 concludes.[3]

[3] Please refer to Appendix A B C D and E for additional materials.

2 Data

To investigate the effect of rainfall shocks on wages, we compile data at the district level from the District Level Database (DLD) for Indian agriculture curated by International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and Tata-Cornell Institute (TCI). We use unapportioned district level data from 1990 to 2017 for 586 districts from 20 Indian states. The DLD from TCI-ICRISAT contains information on wages, crop acreage, fertilizer use, irrigation, number of markets, and rainfall.

2.1 Wages

We use district-level wage information from the TCI-ICRISAT Database for both male and female field labor wages. Wage information is in nominal terms (Indian Rupee (Rs) per day). The data is available at an annual scale for each district and state. To control for inflation over time we deflate the nominal wage rates by the Consumer Price Index (CPI) for agricultural workers.[4] Data on CPI is obtained from the Reserve Bank of India (RBI) Database on the Indian Economy (DBIE) (R. B. o. I. Govt. of India, 2024). Because of the restructuring of states we do not have information for Telangana, Jharkhand, Chhattisgarh, and Uttarakhand for all years in the CPI series obtained from the DBIE. Since we are using state-level CPI averages to deflate the nominal wage rate, we can replace the missing data for the aforementioned states with the corresponding values from the parent state.[5]

2.2 Matching district boundaries

Over time, districts within each state in India have also been reorganized due to political, socio-economic, linguistic, and other reasons. In 1966, there were 313 districts across 16 states (not counting the northeastern states, except Assam, and Jammu and Kashmir). By 2015, four additional states had been formed from these original 16, resulting in a total of 20 states and 571 districts. To maintain consistency in the database for both time series and spatial-temporal analysis, TCI-ICRISAT developed a method to allocate data from newly created districts back to their original 1966 district boundaries. As a result, the data is available

[4]We collapse the monthly CPI data for each state to the annual average. CPI was calculated from 1965-1995 using 1960-61 as the base year, and the series from 1995 to 2017 used 1986-87 as the base year. To ensure comparability, we calculated the conversion factor between the two series by using the CPI values from the two series for the year 1995. We converted the CPI values between 1990-1994 (which had 1960-61 as the base year) by multiplying it with the conversion factor. The final CPI series had 1986-87 as the base year.

[5]Telangana was part of Andhra Pradesh, Jharkhand was part of Bihar, Chhattisgarh was a part of Madhya Pradesh, and Uttarakhand was a part of Uttar Pradesh.

in two versions: an apportioned database using the 1966 district boundaries and an unapportioned database reflecting the current boundaries (as of 2015-16). The apportioned database covers data from 1966 to 2015-16, while the unapportioned version contains data from 1990 to 2015-16. In this paper, we use both versions of the data. For our main district-level analyisis, we use the unapportioned version. We do not make any changes to the database and use it as it is made available by TCI-ICRISAT. While the appportioned database provides a much longer time period for analysis, we prefer using the unapportioned database because it reflects contemporary district boundaries. Estimates derived from this data can inform decision-making at the district level. We use the unapportioned version of the DLD when we conduct supplementary analysis at the household level. We merge several key variables at the district level with household-level data from the India Human Development Survey (IHDS) rounds 1 and 2 (Desai & Vanneman, 2015; Desai et al., 2008). To test for some assumptions that require long-run rainfall data, we also use the apportioned version of the DLD (see section 2.3 and Appendix C).

2.3 Rainfall shocks

Existing research on weather fluctuations uses various definitions of rainfall shocks. Irrespective of the definition, shocks are always defined with respect to a benchmark. Some studies use deviation from historical 'normal' to define positive or negative shocks (for example, Maitra and Tagat (2023)). Other studies have used deviations above the 80th and below the 20th percentiles of the historical rainfall distribution to define positive and negative rainfall shocks (Jayachandran, 2006; Kaur, 2019; Mahajan, 2017). The reference period for identifying the thresholds is nonetheless, some historical rainfall distribution that is governed by the availability of data in the respective study. For instance, Jayachandran (2006) analyses rainfall shock and wages for the time period 1956-87 and uses this period to define the thresholds. Similarly, Kaur (2019) studies a longer time period (1956-2009) using two datasets: World Bank Agriculture and climate dataset for 1956-87; and combinations of the individual rounds of the Indian National Sample Survey (NSS) rounds of 1982, 1983, 1987, 1993, 1999, 2003, 2004, 2005, 2007, and 2009 agricultural years for the period 1982-2009. Kaur (2019) defines the rainfall shock based on the rainfall distribution for each district separately for each dataset using the available time frames to identify the thresholds. On average, the reference period consists of approximately 30 years of rainfall data in the existing literature. This is appropriate to capture long-term climate trends and rests upon the assumption that agents can perfectly retrieve all data relevant to the problem at hand (Malmendier & Wachter, 2024). Under the rational expectations framework, farmers are assumed to form expectations about future rainfall based on past realizations and can be represented by (following Ji and Cobourn (2021)):

$$\mathbf{E}_t[R] = \sum_{s=1}^{T} \beta_s R_{t-s} \tag{1}$$

where R is an independently and identically distributed random variable with mean μ and variance σ^2. The baseline learning mechanism (equation 1) using long-run normals implicitly assumes that given a lengthy time series of previous weather realizations, the effect of any single year on posterior beliefs is relatively small: $\beta_s = 1/T$, under the assumption that farmers have full access (cognitively) to previous T years of rainfall realizations. While this might seem plausible for scientists working on climate models, economic agents such as farmers, engaged in real-time decision making, might not necessarily be able to retrieve all such 'data' accurately. Moreover, it is established that farmers' perceptions about rainfall shocks are based on their historical experiences (Slegers, 2008)- with higher weights often attached to more recent experiences (Ji & Cobourn, 2021). In fact, Arora and Feng (2024) argue that approximately 70 % of farmers in the western frontier of the US corn belt misperceive past weather changes. If forecast limitations constrain farmers even in the US—where meteorological infrastructure and predictive accuracy far exceed those in Africa and Asia—the forecasting challenges facing farmers in the global South, including India, are substantially more severe. Despite recent improvements in rainfall prediction in India, information gaps and accessibility barriers likely persist in these regions.

Alternative learning mechanisms that deviate from the long-run norms have challenged the rational expectations framework. Malmendier and Wachter (2024) reviews the effect of shocks on stock market participation, bond holdings, mortgage choices, home ownership rates, inflation expectations and voting records across US and Europe to identify four features- long-lasting effects, recency bias, context dependence, and robustness to expert knowledge- that reject the rational expectations framework. Following Taylor et al. (1988), Slegers (2008) argues that historical experiences not only shape the memory but also the definition of shocks. There is a tendency for shocks that occurred a long time ago to be less remembered by farmers (Tversky & Kahneman, 1974). This phenomenon is guided by the *availability heuristic*- the effects on expectations and decisions are larger for more recent shocks, and smaller or even negligible for more distant shocks (Ji & Cobourn, 2021). This is driven by the cognitive bias that occurs when farmers overweigh recent events while forming expectations about future conditions (Ji & Cobourn, 2021; Nutsugah, 2025). In terms of equation 1, this can be represented as:

$$\mathbf{E}_t[R] = \sum_{s=1}^{T} \beta_s R_{t-s} \tag{2}$$

$$= \beta_1 R_{t-1} + \beta_2 R_{t-2} + \cdots + \beta_T R_{T-t} \tag{3}$$

Where $\beta_1 \neq \beta_2 \neq .... \neq \beta_T$ and $\beta_1 > \beta_2 > .... > \beta_T$ under recency bias. Recency bias can also be possible if $\beta_s > 0$ when $s \leq S$ and $\beta_s = 0$ when $S < s < T$. Another alternative learning mechanism is the reinforcement strategy where an agent adjusts their expectation by reinforcing the most recent shock i.e. the difference between the most recent realization, R_{t-1} and the expectation prior to that realization:

$$\mathbf{E}_t[R] = \sum_{s=1}^{T} \beta_s R_{t-s} + \gamma[R_{t-1} - \mathbf{E_{t-1}(R)}] \tag{4}$$

$$= \sum_{s=1}^{T} \tilde{\beta}_s R_{t-s} \tag{5}$$

Where $\tilde{\beta}_1 = \beta_1 + \gamma$ and $\tilde{\beta}_s = \beta_s - \gamma\tilde{\beta}_{s-1}$ for $s \geq 2$ and $\gamma > 0$ captures the magnitude of the reinforcement behavior.

These are some of the most common alternative learning mechanisms or heuristics that economic agents use to form expectations about some random event. In the Indian context, where rainfall forecasts have only recently improved, it can be argued that farmer's expectation formation is based upon their subjective beliefs regarding the underlying weather distribution. Kala (2017) develops a model that compares the learning mechanisms under the Bayesian framework with the alternative mechanisms, especially one where farmers attach greater weights to recent realizations (robust learning framework). She finds that the mean-squared error of the model that uses the robust learning framework to predict farmer behaviour is lower than the other Bayesian models. This indicates that in environments characterized by uncertainty, where the underlying distribution of the random variable itself is changing, agents may be relying on alternative heuristics to make important decisions.

Studying the effect of monsoon rainfall shocks on yield, wages, and food prices in India, the optimal lag-length of shocks is identified to be 3 years (Brey et al., 2022). Following the optimal lag-length identified by Brey et al. (2022), and against the backdrop of farmers' relying on alternative heuristics, we redefine the rainfall shock variable in the paper. We use percentile-based thresholds based on the rainfall distribution of each district over the previous 3 years, as opposed to long-run normals, to define rainfall shocks for each district-year pair. A district d is identified as experiencing a positive rainfall shock if the rainfall in year t is greater than the 80^{th} percentile of the rainfall distribution for that district over the previous 3 years. Similarly, a district d experiences a negative rainfall shock if the rainfall in year t is less than the 20^{th} percentile of the 3-year historical rainfall distribution. Due to the rolling nature of the reference period, our definition of rainfall shock helps capture the relativity of shocks based on the available information.

We conduct the above exercise for rainfall during the two major phases of an agricultural season- sowing and harvest phases. Analyzing the effects of only the sowing season can underestimate the overall effect of rainfall shocks on agricultural employment (Sumner et al., 2025). Moreover, since wage information is only available at the annual scale, it is appropriate to examine the nature of shocks over both sowing and harvest phases of an agricultural year. To identify the seasons, we use rice as the benchmark due to its importance and dependence on rainfall. We define the sowing and harvest period using the state-wise crop calendar for rice published by the Indian Council of Agricultural Research (ICAR) (M. o. A. a. F. W. Govt. of India, 2021). Sowing season for rice across the country is between May to July, and October to December is the harvest period for Kharif rice (rainy season).[6] We focus primarily on Kharif rice because this is the most important season for rice production. To construct the seasonal rainfall shock variable for the sowing and harvest periods, we first aggregate the district-wise rainfall for each year for the sowing and harvest months. Then we define the rainfall shocks for each period based on the aforementioned definition.

We provide evidence that points to the presence of recency bias in Appendix D. Using data spanning 313 districts between 1966-2017 from the TCI-ICRISAT District Level Database ("ICRISAT-District Level Data", n.d.), we construct indices of long-term climate normals (count of rainfall shock aggregated for previous 6-10 years, 11-15 years, and 16-20 years) and more recent shock variables (1 to 5 year lagged variables).[7] We test for the effect of each type of rainfall shock (positive, negative) across the two phases (sowing and harvest) and their lagged values, on male and female field labor wages using a panel-fixed effects model. The results provide reasonable evidence that supports the recency heuristic: rainfall shocks exert their primary influence on field labor wages within the first two

[6]There are regional variations in the sowing and harvest months. We select these months because they best reflect the general sowing and harvest phase across most states.

[7]Note that this supplementary analysis is done using apportioned data that traces districts to their 1966 boundaries. Our main analysis is done using unapportioned data that reflects more recent boundary changes.

years, with negligible medium-term effects. However, we still observe some persistent long-term effects (significant effect of rainfall shock event 16-20 years prior to the current period). We also provide estimates when rainfall shocks are defined using historical 30-year distribution as the benchmark (see Appendix C). Ideally, this is what a rational farmer would use to form expectations in an environment with complete information. We can treat the effects estimated using this model as representing a scenario where farmers have full access to information regarding historical rainfall distributions and are agnostic to more recent experiences.[8] However, as argued earlier, this rests upon the critical assumption that farmers can retrieve all relevant information regarding past rainfall distributions. The structural shifts in the Indian monsoon over time challenge that assumption.

[8]Refer to Appendix A to see how the definition of rainfall shocks used in this paper differs from the official forecasts provided by the Indian Meteorological Department.

3 Empirical strategy

3.1 Baseline model

We construct a district-level panel for the selected 20 states, covering the time period from 1993 to 2017. Following earlier literature (Jayachandran, 2006; Kaur, 2019; Mahajan, 2017; Maitra & Tagat, 2024), we employ a panel-fixed effects model to estimate the effect of rainfall shocks on agricultural wages. We consider the district to be our unit of analysis because it captures some salient features of the farm labor market in India. Most rural households are very active in the hired labor market either as sellers or buyers. 98 percent of such employment is through short-term casual wage contracts (Kaur, 2019). Wage rates are gender-specific and do not vary much within a district with laborers having a fair idea of the prevailing wage rate. Therefore, a district can be defined as a distinct labor market in India, especially for agriculture. Although there may be some form of rigidity in the wage rates, they are susceptible to external shocks to labor supply and demand given the short-term nature of most contracts.

We begin by documenting the relationship between rainfall shocks across seasons and agricultural field labor wages for men and women. This forms the baseline model where we estimate the individual and joint seasonal effects on wages. We use a two-way fixed effects model of the following specification:

$$\begin{aligned}
\mathrm{W}_{dt} = {} & \beta_0 + \beta_1 \mathrm{irrigation}_{dt} + \beta_2 \ln(\mathrm{ricearea})_{dt} \\
& + \beta_3 \mathrm{fertiliser}_{dt} + \beta_4 \mathrm{rainfed_rice_system}_{dt} \\
& + \beta_5 PS_{dt} + \beta_6 PH_{dt} + \beta_7 NS_{dt} + \beta_8 NH_{dt} \\
& + \beta_9 (PS_{dt} \times PH_{dt}) + \beta_{10} (NS_{dt} \times NH_{dt}) \\
& + \beta_{11} (PS_{dt} \times NH_{dt}) + \beta_{12} (NS_{dt} \times PH_{dt}) \\
& + \alpha_d + \delta_t + \varepsilon_{dt}
\end{aligned} \tag{6}$$

where W_{it} denotes the log of real wages for field labor in district i in year t. We estimate equation 6 separately for male and female field labor. The variables $PS_{dt}, NS_{dt}, PH_{dt}, NH_{dt}$ denote the indicator variables for positive shocks in sowing season (PS), negative shocks in sowing season (NS), positive shock in harvest season (PH), and negative shock in harvest season (NH), respectively. The reference category for these variables in the normal rainfall category. We are interested in joint effect of shocks across the two seasons on field labor wages. Therefore, the interaction terms capture the four combinations of shocks that are possible in an agricultural year. The model incorporates four interaction terms that capture the joint effects of rainfall shocks across the two agricultural seasons: $(PS_{dt} \times PH_{dt})$, $(NS_{dt} \times NH_{dt})$, $(PS_{dt} \times NH_{dt})$, and $(NS_{dt} \times PH_{dt})$. These terms allow us to examine how the combination of shocks across different phases of the agricultural cycle affects labor market outcomes, recognizing that the timing and sequence of rainfall patterns may have non-additive effects on agricultural productivity and labor demand.

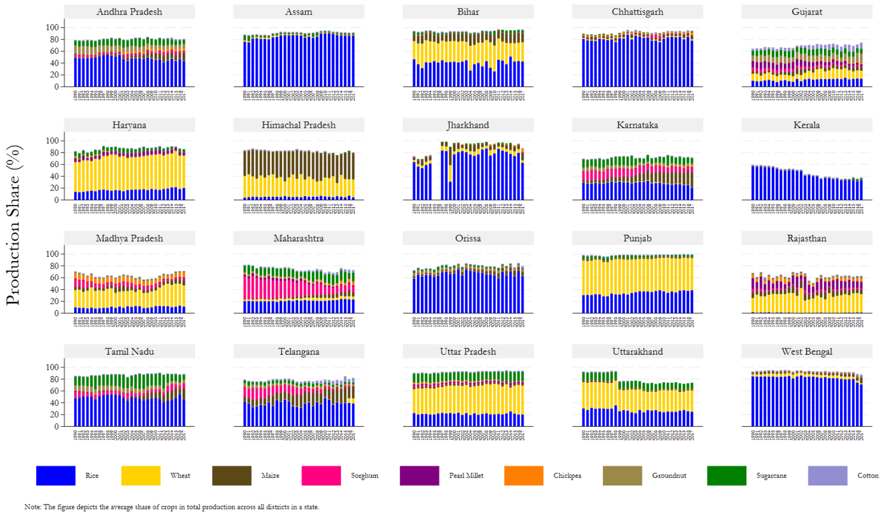
The identification variation within this preferred specification comes from within-district and across districts differences in rainfall shocks over time, conditional on district and year fixed effects. The coefficients of the interaction terms represent the additional effects of joint rainfall shocks across the two phases of agriculture (kharif), beyond their individual main effects, on wages, compared to normal rainfall in both phases. The linear combination of the individual and joint seasonal effects gives the total impact of rainfall shocks on wages. We can compute this from equation 6 by holding the other control variables constant. For example, the marginal effect of the joint negative and positive shocks in the sowing and harvest season is: $\beta_7 + \beta_6 + \beta_{12}$.

Our model includes several control variables that capture agricultural production characteristics and technology adoption. The variable irrigation$_{dt}$ is the natural logarithm of total irrigated area under rice in a district and captures the presence of irrigation infrastructure in the district. $\ln(\text{ricearea})_{dt}$ represents the natural logarithm of total rice cultivation area, capturing the scale of agricultural activity; fertiliser$_{dt}$ is the natural logarithm of fertiliser use (total consumption of nitrogen, phosphorous, and potassium in kg/ha of net cropped area). rainfed rice system$_{dt}$ is a dummy variable indicating districts where rice cultivation primarily depends on rainfall rather than irrigation systems. Rainfed rice cultivation systems are more vulnerable to rainfall shocks. We use rice cultivation as a benchmark to study the effect of rainfall shocks on wages for two major reasons. First, rice occupies an important share in the crop production mix across the 20 states in our sample. Second, among nine major crops, rice is one of the four crops that are most vulnerable to rainfall shocks.[9] We create the rainfed rice system$_{dt}$ variable that equals 1 if the share of irrigated rice cultivation in the district is less than 50 percent. In other words,

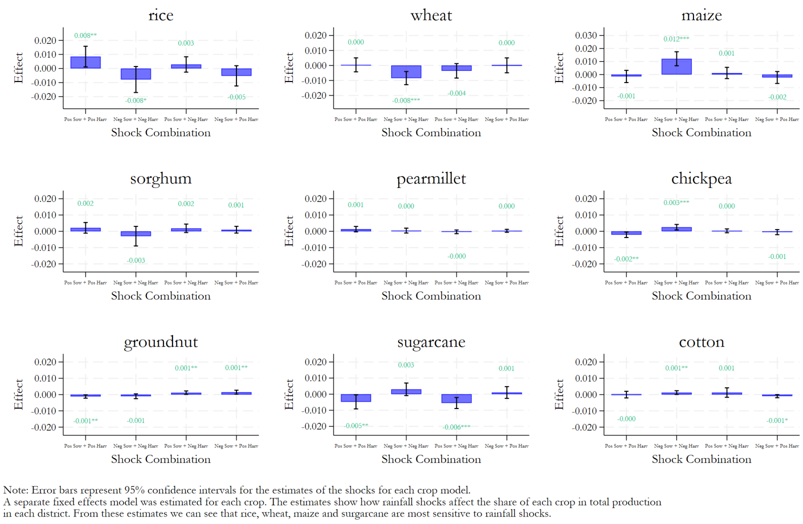
$$\text{Rainfed Rice System}_{dt} = 1, \quad \text{if} \quad \frac{\text{Irrigated Rice Area}_{dt}}{\text{Rice Area}_{dt}} \times 100 \leq 50$$

The specification (equation 6) also includes two-way fixed effects to control for unobserved heterogeneity. District fixed effects (α_d) absorb all time-invariant

[9] Figure 1 validates why our study uses rice cultivation as a benchmark. In figure 1a, we see that rice cultivation (blue bars) accounts for a major share of the total production across several states. Figure 1b reports the sensitivity of crops (share in production) to different rainfall shock combinations. Rice, wheat, maize, and sugarcane are most sensitive to various combinations of rainfall shocks. Given its importance in total production and sensitivity to rainfall shocks, we use information on rice cultivation across major districts as controls in our estimation models.



(a) Crop share in production



(b) Effect of rainfall shock on crop shares

Figure 1: Crop mix and sensitivity to rainfall shocks

characteristics specific to each district, such as soil quality, geographic features, and institutional factors. Year fixed effects (δ_t) capture common macroeconomic shocks, policy changes, and technological developments that affect all districts uniformly in a given year. ε_{dt} represents the idiosyncratic error term, assumed to be independently and identically distributed. We employ cluster-robust standard errors at the district level to account for potential serial correlation and heteroskedasticity within districts over time.

3.2 Sensitivity to other controls

To examine whether the effects of rainfall shocks on wages vary across different agricultural contexts, we extend our baseline specification to include three-way interaction terms that capture heterogeneous treatment effects based on key agricultural characteristics. This approach allows us to test whether the sensitivity of wages to rainfall shocks differs systematically across districts with varying rice acreage and irrigation infrastructure.

We first investigate whether the wage impacts of rainfall shocks vary with the scale of rice cultivation in a district. Districts with larger rice cultivation areas may exhibit different labor market responses to weather shocks due to economies of scale, labor market thickness, and diversification opportunities. The extended specification incorporates three-way interactions between the logarithm of rice area and the joint seasonal shock combinations. We focus on the combination of negative shocks in the sowing season and positive shocks in the harvest season, as it is this combination that has the largest and statistically significant impact on both male and female field labor wages. We estimate the following model specification, separately for field labor wages for men and women:

$$
\begin{aligned}
W_{dt} = {} & \beta_0 + \beta_1 \ln(\text{ricearea})_{dt} + \beta_2 \text{fertiliser}_{dt} + \beta_3 \text{rainfed\_rice\_system}_{dt} \\
& + \beta_4 \text{irrigation}_{dt} + \beta_5 PS_{dt} + \beta_6 PH_{dt} + \beta_7 NS_{dt} + \beta_8 NH_{dt} \\
& + \beta_9 (PS_{dt} \times PH_{dt}) + \beta_{10} (NS_{dt} \times NH_{dt}) + \beta_{11} (PS_{dt} \times NH_{dt}) \\
& + \beta_{12} (NS_{dt} \times PH_{dt}) + \beta_{13} (\ln(\text{ricearea})_{dt} \times NS_{dt}) \\
& + \beta_{14} (\ln(\text{ricearea})_{dt} \times PH_{dt}) + \beta_{15} (\ln(\text{ricearea})_{dt} \times NS_{dt} \times PH_{dt}) \\
& + \alpha_d + \delta_t + \varepsilon_{dt}
\end{aligned}
\tag{7}
$$

We next examine whether access to irrigation infrastructure moderates the relationship between rainfall shocks and wages. Irrigation systems may provide a buffer against adverse weather conditions, potentially reducing the labor market impacts of rainfall variability. The specification with irrigation interactions takes the form:

$$
\begin{aligned}
W_{dt} = \beta_0 &+ \beta_1 \ln(\text{ricearea})_{dt} + \beta_2 \text{fertiliser}_{dt} + \beta_3 \text{rainfed\_rice\_system}_{dt} \\
&+ \beta_4 \text{irrigation}_{dt} + \beta_5 PS_{dt} + \beta_6 PH_{dt} + \beta_7 NS_{dt} + \beta_8 NH_{dt} \\
&+ \beta_9 (PS_{dt} \times PH_{dt}) + \beta_{10} (NS_{dt} \times NH_{dt}) + \beta_{11} (PS_{dt} \times NH_{dt}) \\
&+ \beta_{12} (NS_{dt} \times PH_{dt}) + \beta_{13} (\text{irrigation}_{dt} \times NS_{dt}) \\
&+ \beta_{14} (\text{irrigation}_{dt} \times PH_{dt}) + \beta_{15} (\text{irrigation}_{dt} \times NS_{dt} \times PH_{dt}) \\
&+ \alpha_d + \delta_t + \varepsilon_{dt}
\end{aligned} \tag{8}
$$

The total marginal effect of experiencing both negative sowing shocks and positive harvest shocks depends on the scale of rice cultivation in each district and is calculated, from equation 7, as:

$$
\frac{\partial W_{dt}}{\partial (NS_{dt} \times PH_{dt})} = \beta_6 + \beta_7 + \beta_{12} + (\beta_{13} + \beta_{14} + \beta_{15}) \times \ln(\text{ricearea})_{dt} \tag{9}
$$

The total marginal effect of experiencing both negative sowing shocks and positive harvest shocks depends on the level of irrigation infrastructure in each district and is calculated, from equation 8, as:

$$
\frac{\partial W_{dt}}{\partial (NS_{dt} \times PH_{dt})} = \beta_7 + \beta_6 + \beta_{12} + (\beta_{13} + \beta_{14} + \beta_{15}) \times \text{irrigation}_{dt} \tag{10}
$$

Using the three-way interaction models represented by equations 7 and 8, we estimate the above marginal effects for a range of rice area and irrigation area values. We also report the estimates for different types of irrigation channels- canal, tank, and tubewell irrigation. Subsequently, we explore the role that agricultural markets play in moderating the relationship between rainfall and wages. Finally, we examine the potential mechanisms that influence this relationship by using supplementary data at the household level from the India Human Development Survey (IHDS) rounds 1 (2004-05) and 2 (2011-12) (Desai & Vanneman, 2015; Desai et al., 2008). We model the simultaneous decision-making process that determines labor supply and wages within the framework of an agricultural household model. We use a 3-stage least squares method to estimate the effect of rainfall shocks on household labor supply and their impact on hired wages (refer to Appendix B for a detailed discussion). We also use the household-level information to identify the underlying mechanism through which markets moderate the effect of rainfall shocks on wages.

3.3 Summary Statistics

Table 1 reports the summary statistics of the key variables used in the analysis. Our main estimation sample corresponding to equation 6 is a district-level panel data comprising 11316 observations. The district-level mean wage Rs 146/day for male and Rs 71/day for female field labor respectively. This is the mean nominal wage but we use real wages in the estimation model as described in section 2.1. The mean irrigated area in a representative district from our sample is approximately 54 thousand hectares, with the values ranging from zero to 465 thousand hectares across districts- highlighting the nationwide variation in irrigation coverage, especially for rice. At the same time, we also find that 42 percent of the observations are classified as rainfed rice systems - implying that they are more reliant on rainfall than irrigation. Average acreage of rice cultivation in a district is 95 thousand hectares with wide variation across districts. The average total fertilizer consumption at the district level, combining the values of nitrogen, phosphorus, and potassium, is 170.74 kg/ha.

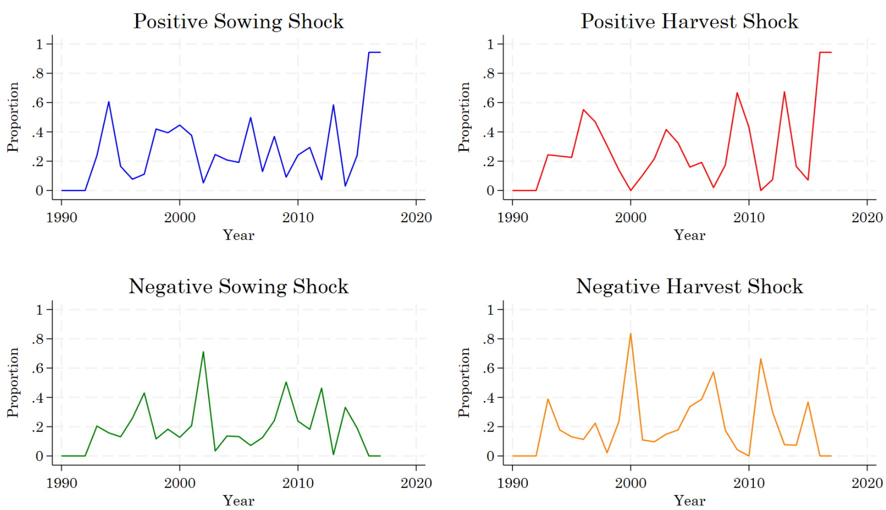
Table 1: Summary Statistics

Variable	N	Mean	SD	Min	Max
Main Variables					
Male field wages (Rs/day)	11,316	145.86	131.00	6.3	1283.89
Female field wages (Rs/day)	11,316	70.62	57.93	1	500
Irrigated area for rice ('000 ha)	11,316	53.55	69.00	0.01	465.10
Rice area ('000 ha)	11,316	94.75	99.03	0.01	918.60
Fertiliser use (kg/ha of NCA)#	11,316	170.74	160.68	0.04	5182.89
Rainfed rice system	11,316	0.418	0.493	0	1
Rainfall Shocks					
Positive Sowing Shock	11,316	0.289	0.453	0	1
Negative Sowing Shock	11,316	0.196	0.397	0	1
Positive Harvest Shock	11,316	0.286	0.452	0	1
Negative Harvest Shock	11,316	0.212	0.409	0	1
Additional Controls					
Total Number of Markets	4,831	14.89	11.86	0	80
Canal irrigation (share)	11,355	33.76	33.51	0	100
Tube irrigation (share)	11,355	42.32	36.85	0	100
Tank irrigation (share)	11,355	14.32	27.07	0	100

Notes: # refers to Net Cropped Area. This table reports the summary statistics of the variables used in the main analysis. These are all district-level variables compiled from the unapportioned TCI-ICRISAT District Level Database. The number of observations refers to the observations in the estimation model for each analysis. In the baseline model, we have 11316 observations, for the robustness checks, we run two separate models to estimate the effect of markets and disentangle the effect of the type of irrigation on wages. The number of observations corresponds to the estimation sample size for the respective model.

The average district-level share in total irrigation is 34 percent for canal irrigation, 42 percent for tubewell irrigation, and 14 percent for tank irrigation. The average number of markets in a district is 14 with wide variation across districts. The total number of markets in our sample ranges from 0 to 80. We have relatively fewer observations for the total number of markets (4831). Table 1 also reports the distribution of rainfall shocks. It ranges from 19.6 percent for negative sowing shocks to 28.9 percent for positive sowing shocks. Figure 2 depicts the temporal distribution of the average share of districts experiencing rainfall shocks- positive and negative- during the sowing and harvest seasons. There has been an increase in the share of districts experiencing positive rainfall shocks in the mid-2010s, and a decrease in the share of districts experiencing negative shocks during the same period. Figure 2 also reveals peaks and troughs in the temporal pattern. For example, the share of districts experiencing negative rainfall shocks during the sowing season was highest in 2002. This also coincides with one of the most severe droughts in India's history- driven mainly by extremely low rainfall in July (Chuphal et al., 2024). Similarly, during the post-monsoon season in 2000, several districts experienced deficient rainfall, and this is reflected by the high share of districts experiencing negative rainfall shock during the harvest season of 2000.

Figure 2: Average share of districts experiencing rainfall shocks



Note: The figure reports the average number of districts experiencing rainfall shocks. We collapse the district-level data by year to arrive at these figures.

In addition to the data used in the main analysis, we also discuss underlying mechanisms that could be driving the relationship between rainfall shocks and wages. It depends upon the labor-leisure trade-off in household labor supply decisions. We discuss the data in detail in section 5.1 and Appendix B. For brevity, we do not report the summary statistics of the variables used in the supplementary analysis here. In the next section, we discuss the results from our analysis.

Table 2: Effect of rainfall shock on field labor wages

Variable	**Male** (1)	**Female** (2)
Irrigation (log)	-0.004	-0.004
	(0.012)	(0.010)
Rice area (log)	0.065**	0.024
	(0.032)	(0.037)
Fertiliser (log)	0.062**	0.055**
	(0.030)	(0.025)
Rainfed rice system (Yes=1)	0.054	-0.015
	(0.040)	(0.038)
Positive sowing season shock	-0.006	-0.017
	(0.014)	(0.013)
Positive harvest season shock	0.034**	0.037***
	(0.015)	(0.014)
Negative sowing season shock	0.001	0.006
	(0.013)	(0.013)
Negative harvest season shock	-0.006	-0.001
	(0.015)	(0.013)
Positive Sowing × Positive Harvest	-0.054**	-0.074***
	(0.027)	(0.025)
Negative Sowing × Negative Harvest	0.029	0.000
	(0.027)	(0.025)
Positive Sowing × Negative Harvest	0.035	0.007
	(0.024)	(0.021)
Negative Sowing × Positive Harvest	-0.086***	-0.083***
	(0.028)	(0.026)
Observations	11,316	11,316
Districts	542	542
Mean Wage (Rs/day)	145.9	70.6
Year FE	✓	✓
District FE	✓	✓

Notes: Robust standard errors in parentheses, clustered at district level. Reference category: Normal rainfall in both seasons. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Column 1 and 2 were estimated separately. We use the model specification stipulated in equation 6 to estimate the models in this table.

4 Results and Discussion

4.1 Baseline Results

Table 2 represents the estimates of the effect of rainfall shocks on wages based on the model specification outlined in equation 6. We present the full model specification that includes various control variables, district and year fixed effects. Our final estimation sample consists of 11316 observations from 542 districts across the 20 states between 1993-2017. We also report the mean nominal wages for field labor for both men and women. Controls for fertilizer use exhibit significant positive associations with wages for both men and women. This positive association between fertilizer use and wages is consistent with literature showing that fertilizer and labor are complementary inputs in agricultural production. Higher fertilizer application typically requires additional labor for application, crop management, and harvesting of increased yields, thereby increasing labor demand and wages (Jha et al., 2024). We also report that a percentage point increase in rice area in the district results in a 6.5 percent increase in male wages. This can be attributed to the increase in demand for labor that might drive up wages for field labor. However, our model estimates suggest that this is only true for male field labor wages. Examining the effect of rainfall shocks, we find that most individual season shocks are not statistically significant- except for positive shocks in the harvest season. Earlier studies have shown that individual season shocks might underestimate the overall effect of rainfall shocks on agriculture (Sumner et al., 2025). Therefore, we examine the joint effect of rainfall shocks across the sowing and harvest seasons. The coefficient on Positive Sowing × Positive Harvest for female field labor wages implies that when both the sowing and harvest seasons are wetter than normal, women's daily wages are an additional 7.4 percent lower than what would be predicted from the sum of individual effects. The coefficient on Negative Sowing × Positive Harvest for women indicates that when a dry sowing season is followed by excess rainfall at harvest, women's wages fall by an extra 8.3 percent beyond the individual impacts of each shock. Similarly, for men, the Negative Sowing × Positive Harvest interaction shows that this same combination of a dry sowing season and a wet harvest reduces men's wages by an additional 8.6 percent relative to the sum of the separate dry-sowing and wet-harvest effects.

While individual regression coefficients reveal the partial effects of isolated seasonal shocks, the linear combination approach captures the total marginal effect of joint shock scenarios that farmers actually experience. In table 3, we report the total marginal effect of each type of joint seasonal shocks by adding their respective coefficients from table 2. The estimates reveal that the most pronounced and statistically significant wage impacts arise under two specific joint-shock scenarios. First, when a dry sowing season is followed by excess harvest rainfall, women's wages decline by Rs 2.88 per day and men's by Rs 7.58 per day (4.1 percent and 5.2 percent, respectively).[10] This large negative effect likely reflects the dual disruption of planting and harvesting schedules—insufficient early-season moisture undermines crop establishment, and subsequent heavy rains waterlog fields, hampering harvesting operations and reducing labor productivity. Second, for women only, a wet sowing season followed by a dry harvest leads to a 1 percent reduction in wages (Rs 0.74/day), implying that inadequate harvest rains after favorable sowing conditions shift labor demand away from women's typical post-sowing tasks. Although, the magnitude of this effect is relatively small compared to the combination of a dry sowing and wet harvest season. These results underscore that joint seasonal shocks exert gender-differentiated pressures on agricultural wages, with women particularly vulnerable to mixed-shock environments and both genders suffering steep losses when sowing season rainfall deficit precedes harvest-season excesses. Given the relatively larger impact of a negative sowing season shock and positive harvest season shock on both male and female field labor wages, we discuss several other potential channels that could moderate their effect on wages.

Table 3: Total effect of rainfall shocks across sowing and harvest seasons

	Female		Male	
Sowing × Harvest	Coeff.	Effect (Rs/day)	Coeff.	Effect (Rs/day)
Negative × Negative	0.005	0.334	0.024	3.504
Negative × Positive	-0.041***	-2.88***	-0.052***	-7.58***
Positive × Negative	-0.010***	-0.74***	0.023	3.33
Positive × Positive	-0.054	-3.81	-0.026	-3.84

Notes: * p<0.10, ** p<0.05, *** p<0.01. Effects calculated using baseline model coefficients (table 2). Effect columns show change in Rs/day which was estimated based on the sample mean of the nominal wages for men and women field labor. Given the log-linear model specification in equation 6, the effect is calculated by multiplying the coefficient of the total effect by the mean wage.

4.2 Effect of irrigated area

In the baseline specification, we use the area under irrigated rice as an additional control. We do not find any statistically significant association between irrigated area under rice and wages using equation 6. However, several studies have shown that irrigation infrastructure can reduce the vulnerability of agricultural outcomes to rainfall fluctuations (Brey et al., 2022; Gatti et al., 2021). We explore this channel by estimating how much the effect of rainfall shocks are moderated by varying

[10] We use the average nominal wage for men and women from the estimation sample to estimate the wage effect in Rs/day.

degrees of irrigated rice area across districts. We employ the model represented by equation 8 to estimate the three-way interactions between negative sowing season shock, positive harvest season shock, and rice area under irrigation.

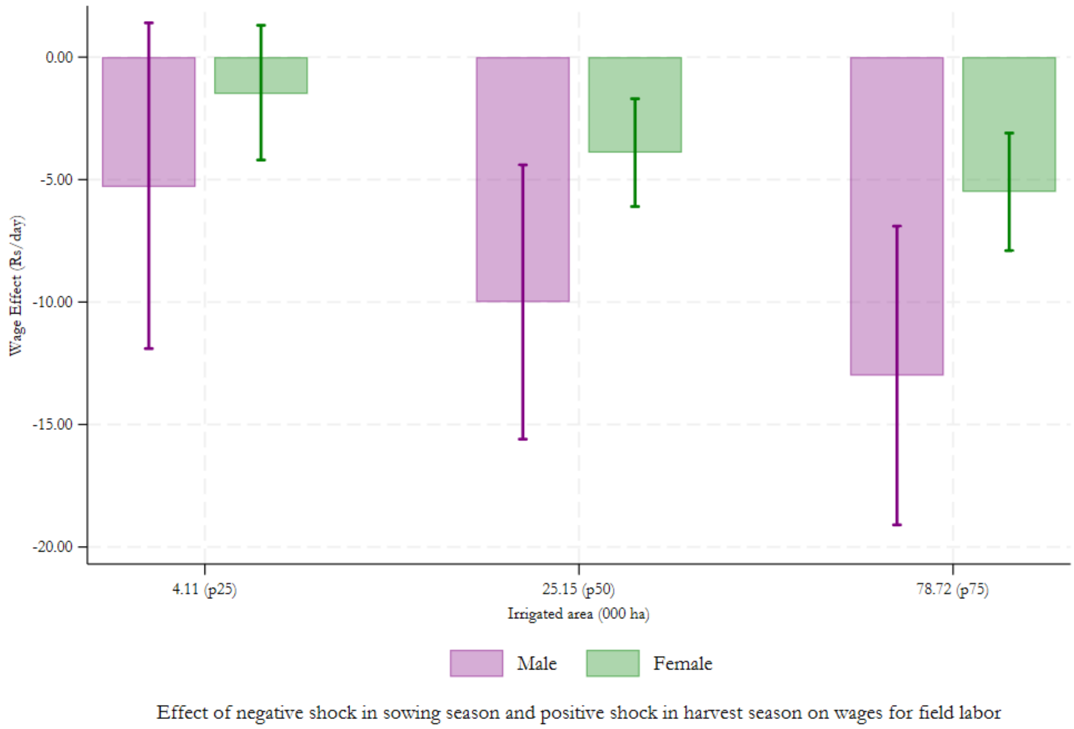


Figure 3: Sensitivity of rainfall shock to irrigated area

Note: The plot represents the total effect of the three-way interaction term between negative shock in the sowing season and positive shock in the harvest season, and irrigation intensity. The estimates are based on coefficients obtained from the model used to test the sensitivity of the effect of rainfall shocks on wages across districts with varying degrees of irrigation intensity. Vertical line represent the 95% confidence intervals. All effects are relative to normal rainfall conditions.

In table 4 the three-way interaction indicates that each additional unit of log irrigated area amplifies the negative wage effect of the negative sowing and positive harvest shock combination by 3.9 percentage. In other words, areas with more extensive irrigated rice area experience more severe wage penalties when this particular joint shock occurs. Similarly, higher irrigation levels worsen the wage impact of negative sowing and positive harvest shocks for women, though the effect is smaller in magnitude and less precisely estimated. In figure 3 we provide estimates of the total marginal effect of the shock combination on male and female field labor wages across different percentiles of rice cultivation under irrigation. We see

Table 4: Sensitivity of the effect to area under irrigation

Variable	**Male Wages**	**Female Wages**
Main Effects		
Rice area (log)	0.064*	0.024
	(0.032)	(0.037)
Fertiliser (log)	0.064**	0.055**
	(0.030)	(0.025)
Rainfed Rice System (Yes=1)	0.055	-0.015
	(0.040)	(0.038)
Irrigated area (log)	-0.007	-0.003
	(0.012)	(0.011)
Positive sowing season shock	-0.007	-0.016
	(0.014)	(0.013)
Negative sowing season shock	-0.013	0.010
	(0.021)	(0.021)
Positive harvest season shock	-0.011	0.032
	(0.022)	(0.021)
Negative harvest season shock	-0.005	-0.001
	(0.015)	(0.013)
Joint-seasonal effects		
Negative sowing × Irrigated area	0.005	-0.002
	(0.005)	(0.005)
Positive harvest × Irrigated area	0.017***	0.002
	(0.006)	(0.006)
Negative sowing × Positive harvest	0.015	-0.036
	(0.043)	(0.042)
Positive sowing × Positive harvest	-0.058**	-0.076***
	(0.027)	(0.025)
Negative sowing × Negative harvest	0.028	0.000
	(0.027)	(0.025)
Positive sowing × Negative harvest	0.035	0.007
	(0.024)	(0.021)
Interaction with irrigated area		
(Negative sowing × Positive harvest) × Irrigated area	-0.039***	-0.019*
	(0.011)	(0.011)
Observations	11,316	11,316
Districts	542	542
Mean Wage (Rs/day)	145.86	70.62
Year FE	✓	✓
District FE	✓	✓

Notes: Three-way interaction allows negative sowing × positive harvest effects to vary with irrigated area. Robust standard errors are in parentheses and clustered at the district level. * p<0.10, **p<0.05, *** p<0.01

that the effect of the shocks are amplified with an increase in irrigated area under rice. While this might appear counter-intuitive as irrigation is expected to insulate agriculture from rainfall fluctuations, our findings are in line with the existing literature (Mahajan, 2017). While irrigation reduces the impact of rainfall shocks on yield, its impact on wages operates through a different mechanism and might even exacerbate the negative effects. This is primarily because districts that have better irrigation facilities engage in more intensive agricultural activities- including the cultivation of riskier crops as well as greater dependence of local population on agriculture in these areas. Moreover, as Mahajan (2017) argues, workers often migrate to districts with better irrigation infrastructure, resulting in an increase in labor supply that can further depress wages. Immigration to these districts might be higher when neighboring districts experience adverse rainfall conditions. With neighboring districts usually experiencing similar weather patterns,it might be plausible that the districts that have better irrigation infrastructure attract additional labor during adverse rainfall years. In fact, citing the National Sample Survey Organization's (NSSO) national survey of migration (NSS 64th round) conducted during July 2007 through June 2008, Zaveri et al. (2020) reports that most movements are either to a different district within the same state or a different state compared to within the same district. They find that the availability of irrigation (captured by irrigated area) reduces the probability of migration from the district.

4.2.1 Source of irrigation

To provide futher evidence of the role of irrigation in moderating the effect of rainfall shocks on wages, we estimate model 8 for the different types of irrigation. We use the share of tube well, canal and tank irrigation in total irrigated area as explanatory variables. The share of tank irrigation is used as the reference category. We estimate the interaction between the negative sowing and positive harvest shock, and the share of different types of irrigated area in the district.[11]

Figure 4 reveals a striking pattern where modern irrigation infrastructure amplifies rather than mitigates the negative wage effects of negative sowing season and positive harvest season rainfall shocks. At the 25th percentiles of tubewell and canal irrigation shares, wage effects remain relatively neutral or even slightly positive for both men and women. However, as tubewell shares increase, wage penalties become progressively more severe, reaching approximately -15 Rs/day for males and -8 Rs/day for females. Effects of canal irrigation are qualitatively similar but not statistically significant. These results are in line with our earlier

[11] In figure 4 we plot the estimates of the total marginal effect of the joint seasonal rainfall shocks for different shares of irrigation from tubewell and canals. The reference category is tank irrigation. The regression table can be made available upon request.

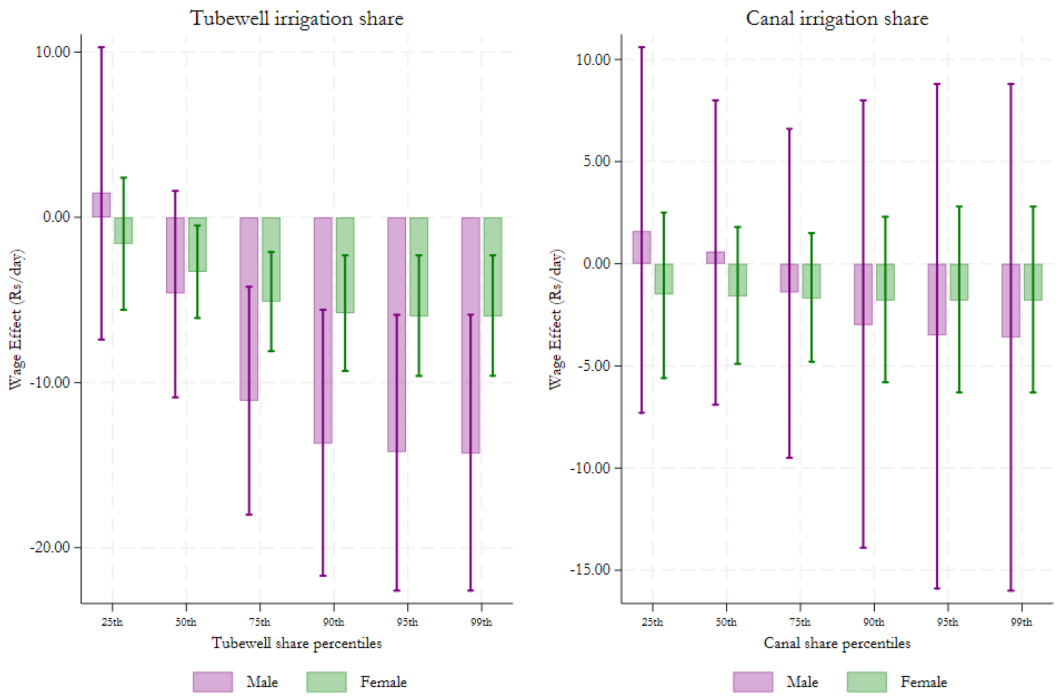


Figure 4: Type of irrigation and effect on wages

Note: The figure reports the total impact of negative sowing and positive harvest shocks moderated by types of irrigation source. The values are estimated based on the mean wages for field labor for men and women respectively. Tank irrigation is used as the reference category. Error bars represent the 95% confidence intervals. The estimates are based on the model used to test for the effect of source of irrigation.

findings for irrigated area under rice cultivation (see figure 3). Our findings are similar across gender, with the effects being larger in absolute terms for men.

The vulnerability of tubewell systems likely stems from their encouragement of intensive, specialized cropping patterns that become more susceptible to disruption when seasonal rainfall deviates from expected patterns. Zaveri et al. (2020) also finds that areas irrigated by wells have a lower probability of migration and those irrigated by surface water have a higher probability. We can translate these findings to suggest that areas that have greater irrigated area under wells are more actively engaged in agriculture with significant sunk costs involved that make shifting out of agriculture difficult during adverse shocks. These results highlight a fundamental issue in irrigation policy: modern infrastructure designed to reduce rainfall dependence may actually create unintended spillovers in other sectors of the agricultural economy-such as exacerbating the negative effect of rainfall shocks on wages.

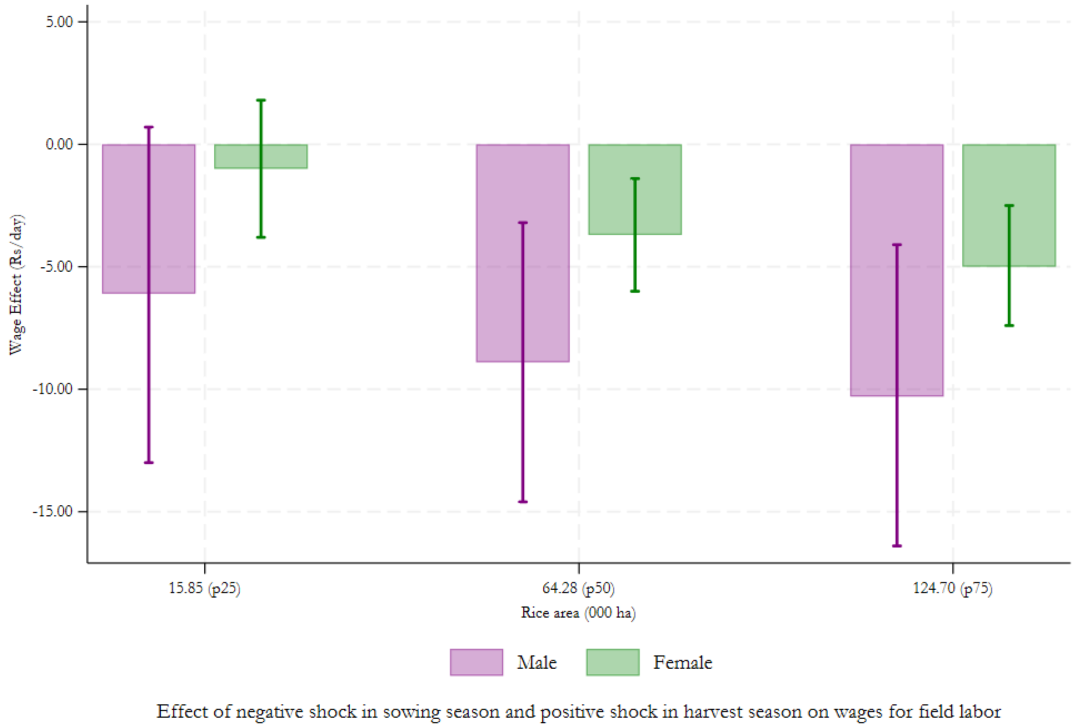


Figure 5: Sensitivity of rainfall shock to rice area

Note: The plot represents the total effect of the three way interaction between negative shock in the sowing season and positive shock in the harvest season and rice area. The estimates are based on the coefficients obtained from the model used to test the sensitivity of the effect of rainfall shocks on wages across districts with varying degrees of rice cultivation intensity. Vertical bars represent the 95 % confidence intervals. All effects are relative to normal rainfall conditions.

4.3 Sensitivity to rice area

Given our focus on rice production as a benchmark for measuring the vulnerability to rainfall variability, we also conduct a sensitivity analysis of the impact of the joint negative sowing and positive harvest season shock for different levels of rice acreage. Figure 5 depicts the total marginal effects of joint shock estimated using the model specified in equation 7. Estimates from the model are reported in table 5. We use the mean wage values for men and women to estimate the total effect in nominal terms (Rs/day). We find that the negative effect of sowing season negative and harvest season positive shocks are amplified in districts with larger areas under rice cultivation. These effects can be identified by the variation in the share of rice in total crop production as depicted in figure 1a. We find that the effect is not statistically significant at the 25th percentile of area under rice cultivation but significant at the 50th and 75th percentiles. The total effect ranges from Rs. 8/day to Rs. 11/day for men, and Rs 3/day to Rs 5/day for women.

4.4 Other potential channels

In addition to area under rice, irrigated area and different sources of irrigation, we explore another possible channel that can influence the effect of rainfall shocks on wages of agricultural field labor- access to markets.

4.4.1 Access to markets

The relationship between market power and prices that farmers receive has been well documented in the growing body of industrial organization literature (Bekkerman & Taylor, 2020; Chatterjee, 2023; Sexton & Xia, 2018; Sexton & Zhang, 2001). The general conclusion is that lower market power, greater competition, and easier and/or cheaper access to markets improve the price that farmers receive for their produce. Such improved prospects for farmers when faced with favorable conditions to sell their output can also translate to higher wages for agricultural labor (Jacoby, 2016). Jacoby (2016) find that nominal wages for manual labor across rural India increase with higher agricultural prices. If access to markets can ensure better prices then we can argue that wages might increase in such situations. We empirically test this hypothesis by estimating the effect of rainfall shock on wages using a three-way interaction between negative sowing season, positive harvest season shock, and the total number of agricultural markets in a district.

Figure 6 shows the total marginal effect of the shock combination for a range of total number of markets at the district-level. We find that relative to districts experiencing normal rainfall, the wages are lower in districts with fewer markets (25th percentile), but higher in districts with more markets (90th percentile and beyond) when faced with the negative $\times$ positive rainfall shock combination.[12] Despite the correlation between productivity and the number of markets in a district, our estimates suggest that the price-wage pathway, as suggested by Jacoby (2016), might help dampen some of the negative effects on wages that we estimated earlier. We discuss this mechanism further in section 5.2.

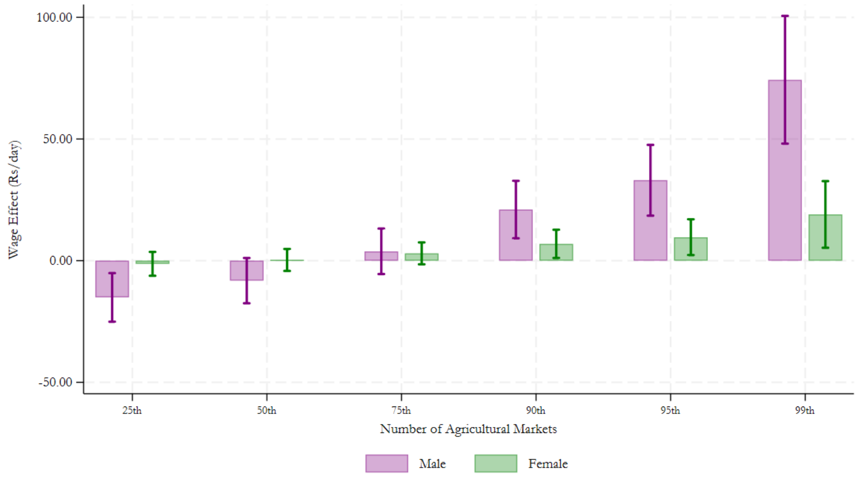
[12] Chatterjee (2023) reports that controlling for size, cropped area, and population of districts, more productive districts have a higher number of markets. This could potentially confound our estimates as well.

Table 5: Sensitivity of the effect to area under rice cultivation

Variable	**Male Wages**	**Female Wages**
Main Effects		
Rice area (log)	-0.004	-0.004
	(0.012)	(0.010)
Fertiliser (log)	0.062**	0.055**
	(0.030)	(0.025)
Rainfed Rice System (Yes=1)	0.053	-0.015
	(0.040)	(0.038)
Irrigated area (log)	0.060*	0.030
	(0.032)	(0.036)
Positive sowing season shock	-0.005	-0.017
	(0.014)	(0.013)
Negative sowing season shock	-0.022	0.034
	(0.032)	(0.032)
Positive harvest season shock	-0.015	0.092**
	(0.037)	(0.037)
Negative harvest season shock	-0.005	-0.001
	(0.015)	(0.013)
Joint-seasonal effects		
Negative sowing × Rice area	0.006	-0.008
	(0.007)	(0.007)
Positive harvest × Rice area	0.013	-0.014
	(0.009)	(0.009)
Negative sowing × Positive harvest	0.033	-0.068
	(0.069)	(0.070)
Positive sowing × Positive harvest	-0.054**	-0.074***
	(0.027)	(0.025)
Negative sowing × Negative harvest	0.028	0.001
	(0.027)	(0.025)
Positive sowing × Negative harvest	0.034	0.009
	(0.024)	(0.020)
Interaction with rice area		
(Negative sowing × Positive harvest) × Rice area	-0.031**	-0.004
	(0.015)	(0.016)
Observations	11,316	11,316
Districts	542	542
Mean Wage (Rs/day)	145.86	70.62
Year FE	✓	✓
District FE	✓	✓

Notes: Three-way interaction allows negative sowing × positive harvest effects to vary with rice area. Robust standard errors in parentheses, clustered at district level. * p<0.10, ** p<0.05, *** p<0.01

Figure 6: Effect of access to markets on field labor wages



Note: The figure reports the total impact of negative sowing x positive harvest shocks moderated by the number of agricultural markets in a district. The values are estimated based on the mean values of wages for field labor for men and women, respectively. Error bars represent 95 % confidence intervals. The estimates are based on the model used to test for the effect of markets (results can be made available upon request). Only those districts were used in the estimation sample that had information for atleast 10 years. The representative values fo each percentile are 7, 11, 18, 28, 35 and 39.

5 Mechanisms

5.1 Labor supply and demand

Our analysis thus far has focused on the relationship between wages for hired field labor and rainfall shocks at the district level. However, the underlying mechanism driving these outcomes is best understood through the lens of the agricultural household model, which explicitly recognizes that households are both producers and consumers, and that their labor supply and wage outcomes are jointly determined. In this framework, the classical labor-leisure trade-off is embedded within a broader system where production and consumption decisions are interdependent and respond to both market signals and exogenous shocks such as rainfall.

Jayachandran (2006) argues that above-normal rainfall increases agricultural productivity and below-normal leads to a decline in productivity. When households anticipate above-average rainfall, this can act as a catalyst for agricultural production, increasing the marginal productivity of labor and, consequently, the demand for both family and hired labor. The agricultural household model highlights that labor supply responses to such shocks are not determined by the labor-leisure trade-off in isolation, but are shaped by the interaction of the income effect and the substitution effect within a system where wages and labor supply are endogenously linked. The income effect captures how changes in wages or farm profits alter a household's purchasing power and, therefore, its preference for leisure versus labor. The substitution effect, on the other hand, reflects how changes in wages affect the opportunity cost of leisure, incentivizing households to reallocate time toward labor when wages rise.

In the event of an 'above normal' rainfall shock, the substitution effect may encourage households to supply more labor, as the opportunity cost of leisure increases with higher wages and greater labor demand. Simultaneously, the income effect—arising from increased farm profits—may reduce the need to supply additional labor, as households can achieve higher income with the same or even less effort. Conversely, a rainfall deficit may prompt households to supply more labor to supplement lost income (income effect), but the lower opportunity cost of leisure (substitution effect) could dampen this response, or even lead to a reallocation of labor away from agriculture toward less risky activities.

The agricultural household model provides a nuanced framework for understanding how these two forces—income and substitution effects—operate within a system where labor supply and wages are determined simultaneously. Rather than assuming one effect dominates, our analysis investigates the conditions under which either the income or substitution effect prevails, and how their interplay shapes both household labor supply and equilibrium wage outcomes in the face of rainfall shocks. By modeling these relationships jointly, we are able to capture the full general equilibrium response of rural labor markets to weather variability. Appendix B provides a detailed analysis of the empirical estimation of this mechanism. In table 6 we report the total effect on labor supply and wages that was estimated from our household level model (Equations 11a and 11b) using a three-stage least squares (3SLS) procedure (Zellner & Theil, 1962). Following the narrative from our district-level analysis, we focus on the effect of shocks across both agricultural seasons. In particular, we are interested in estimating the effect of a negative sowing × positive harvest shock on a household's labor supply decision and wage offered for hired labor. Deficit rain during sowing season reduces soil moisture, and causes inadequate crop development and poor germination; while excess rain during the harvest season results in waterlogging, crop diseases, delayed harvesting, and physical damage to crops. Both shocks result in conditions that adversely affect crop yield and farm incomes.

Following the agricultural household model framework—where labor supply and wage decisions are jointly determined by both income and substitution effects in response to rainfall shocks—the results in Table 6 support several key mechanisms. When both sowing and harvest seasons experience favorable rainfall, the observed effects on labor supply and wage are negligible, suggesting that the pos-

Table 6: Total Effects of Rainfall Shock Combinations

Model	**Shock Combination**	**Coefficient**	**SE**
Labor Supply	Positive Sowing × Positive Harvest	0.031	(0.114)
	Negative Sowing × Negative Harvest	-0.050	(0.060)
	Positive Sowing × Negative Harvest	-0.178***	(0.051)
	Negative Sowing × Positive Harvest	0.051	(0.159)
Hired Wage	Positive Sowing × Positive Harvest	-0.040	(0.208)
	Negative Sowing × Negative Harvest	0.023	(0.120)
	Positive Sowing × Negative Harvest	-0.193*	(0.111)
	Negative Sowing × Positive Harvest	-0.445**	(0.224)

Notes: * p<0.10, ** p<0.05, *** p<0.01
The table reports the total effect of experiencing specific combinations of sowing and harvest season rainfall shocks simultaneously. We employ a simultaneous equation modeling framework to estimate the impact of rainfall shocks on labor supply and labor wages. Errors are clustered at the district level and reported in parentheses. Estimation is via three-stage least squares (3SLS) process. Typically, the endogenous explanatory variables are dependent variables from other equations in the system. The original model results are in the Appendix B.

itive income effect (households are wealthier, reducing their need to supply labor) is nearly offset by the substitution effect (higher wages make supplying labor more attractive). Similarly, negative shocks in both seasons yield only small changes, consistent with a scenario where increased labor supply (income effect) is counterbalanced by limited demand and stagnant wages (muted substitution effect). The interplay of these effects becomes most visible when shocks are different across the two agricultural phases.

When sowing season rainfall is favorable but harvest rainfall is poor, households experience an income shock at the time of harvest, which theoretically triggers an income effect that encourages them to increase their labor supply in order to compensate for reduced agricultural earnings. However, this negative harvest also diminishes the demand for farm labor and depresses local wages, activating a substitution effect whereby the lower opportunity cost of leisure makes working less attractive. If the substitution effect dominates, as suggested by the observed declines in both labor supply and wage, households end up reducing their supplied labor despite needing more income, because market opportunities have dried up and the incentive to work for low wages is weak. Conversely, when there is a deficit in rainfall in the sowing season, but excessive rainfall during harvest season, the initial income shock prompts households to seek out more wage labor (income effect). But if labor demand does not recover due to excess rain in the harvest season, failing to absorb all the labor supplied, the labor market experiences an excess supply situation. Although the total change in labor supply is muted or insignificant, the persistence of an overabundance of willing workers relative to available jobs leads to a significant drop in local wages, reflecting the dominance of the income effect. These results underscore that, within rural labor markets subject to weather volatility, the strength and direction of income and substitution effects depend critically on the timing and composition of rainfall shocks, and that these effects can amplify or offset each other in shaping household labor and wage outcomes. The household-level analysis enables the decomposition of observed district-level wage effects into the interplay of labor supply decisions and wage determination at the level of individual families. For example, the marked wage declines observed in the joint-shock scenario of dry sowing coupled with excess harvest rainfall—where district panel results showed the largest and most robust negative impact on both men's and women's wages—are shown at the household level to arise from the interaction of income and substitution effects.

5.2 Markets, price and wages

In section 4.4.1, we identified that access to markets has the potential to dampen the wage-reducing effect of rainfall shocks, particularly negative sowing and positive harvest season shocks. We argued that the price-wage pathway was driving this result. We were, however, unable to explore this pathway using the district-level data. To verify this, we once again exploit the information available in the IHDS I and II datasets (Desai & Vanneman, 2015; Desai et al., 2008). We use information on the market price of rice and wheat, hired wage rates, and total number of markets in a district. First, we observe that the market price of rice and wheat is positively associated with the number of markets. We then examine whether the market prices of rice and wheat affect the hired wage rate. We also control for the level of markets in a district. In column 4 of Table 7, we see that the market price of rice has a positive association with the hired wage rate. We find that the relationship is negative between the price of wheat and wage rate but it is not statistically significant. At the same time, we also find that the number of markets does not affect wages. From this we can argue that the effect of markets on wages that we identified earlier was being driven by the price-wage pathway. Although the endogeneity between productivity and the distribution of markets might threaten our analysis, we can still argue that providing access to more markets or increasing the number of markets can improve the wages for agricultural labor. This effect is predominantly operating through the price-wage pathway.

Table 7: Price-wage and markets-price pathways

	Rice Price	**Wheat Price**	**Wage**
Number of markets	0.026*** (5.35)	0.015** (2.76)	0.024 (0.69)
Size of holding	0.005 (1.54)	0.004 (1.79)	0.137*** (9.18)
Fertilizer expenses	0.018*** (3.85)	0.005 (1.29)	0.442*** (21.03)
Equipment expenses	0.020*** (3.89)	-0.002 (-0.47)	0.267*** (13.02)
Rice price			0.360*** (5.29)
Wheat price			-0.017 (-0.22)
Observations	9203	9124	5456
State FE	✓	✓	✓
Time trend	✓	✓	✓

Notes: t-statistics are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01
The table reports the price-wage and price-market pathways that were discussed as mechanisms governing the effects in section 4.4.1. Each column represents a log-log regression model. In columns 2 and 3, we estimate the relationship between the market price of rice and wheat and access to markets. In column 4, we estimate the wage-price pathway. All errors were clustered at the Primary Sampling Unit level, and all variables are natural log transformations. Therefore, the estimates can be interpreted as elasticities.

6 Policy implications

The findings of this study have important policy implications for agricultural and labor markets in India. Firstly, defining rainfall shocks based on local and recent rainfall patterns rather than historical means provides a more realistic foundation, especially when forecasts are not easily accessible to farmers, despite being available (Palit, 2025). Therefore, this study provides a baseline understanding of how rainfall shocks can influence agricultural labor markets when farmers do not have access to real-time forecasts. [13] Until efforts to provide real-time accurate forecasts are available nationwide, farmers will rely on traditional heuristic-based approaches to forming expectations about the weather. Using the previous 3-year rainfall patterns as a benchmark to define shocks can guide policymakers in understanding how farmers are likely to behave during such shock scenarios. Against this backdrop, we find that a combination of negative shocks in the sowing season, followed by a positive shock in the harvest season, has the largest and statistically significant impact on both male and female field labor wages. We also observe that wage declines are more pronounced in areas with greater irrigation infras-

[13] In recent years, there has been a significant improvement in rainfall forecasts by public and private sector stakeholders- in terms of both accuracy and reach. Some notable examples include the IMD Mausam App and SMS delivery of AI-based weather forecasts directly to farmers (Sanders, 2025).

tructure. Therefore, policies that are aimed at improving irrigation infrastructure might have an unintended consequence on the labor markets. By increasing labor migration towards districts that have better irrigation infrastructure (increasing the labor supply), wages are depressed further.

Therefore, policymakers must consider the feedback mechanisms that result in lower wages for field laborers. Public work programs like the National Rural Employment Guarantee Scheme (NREGS) can provide alternative employment opportunities that might reduce the negative impact on wages for field labor. Several studies have shown that the NREGS can buffer the negative impact of rainfall shocks on various outcome indicators, such as instances of domestic violence in a district (Sarma, 2022); children's long-term health outcomes(Dasgupta, 2017); and human capital accumulation, especially for women (Maitra & Tagat, 2024). Employment guarantees can also support farmers in managing agricultural production risks, akin to crop insurance programs.Gehrke (2019) argues that the NREGS, by providing additional employment opportunities, reduces households' uncertainty about future income streams. This enables them to engage in riskier but more profitable crop production. Our results suggest that districts with better irrigation infrastructure should also invest more in providing alternative employment opportunities to reduce the negative effect of excess labor supply, during a negative sowing and positive harvest shock year, on field labor wages.

We find that market access is another important channel that can buffer the negative effects of a negative sowing and positive harvest shock on wages. Expanding rural market access and connectivity is crucial, as better access is positively associated with higher prices for rice and wheat. Higher prices, especially for rice, also have a positive effect on the wages for hired labor (see table 7). State-level marketing laws in India are inherently prohibitive in nature as they restrict farmer-intermediary transactions within a state. This effectively reduces the number of markets available to a farmer, often resulting in the concentration of market power in the hands of a few buyers. Our results highlight the positive effect of competition on the price of rice and wheat, and hired wages. This finding is crucial to understanding how competition in agricultural markets can facilitate farmers' adaptation to weather fluctuations. Kochhar et al. (2025) uses border-discontinuity design to form market pairs that are in proximity to each other but on separate sides of a state border to see how competition influences adaptation behavior among farmers. They find that i) the positive effect of competition on prices is higher after a climate shock, and ii) farmers in high competition areas increase their input usage (indicating climate adaptation). Our results also show that a similar mechanism is at play and therefore highlight the role that markets can play in mitigating the negative effect of rainfall shocks on wages. Two major takeaways from the results in this paper are: 1) in the absence of access to rainfall forecasts, farmers are more likely to use recent historical experiences to form expectations and make agricultural production decisions; 2) areas with better irrigation facilities might need to also invest in alternate employment opportunities to prevent an excess supply of labor during shock years to reduce the downward pressures on field labor wages, and 3) access to a larger number of markets can, through the higher price-wage relationship, reduce the negative impact of a negative sowing and positive harvest season shock on wages for hired field labor.

7 Conclusion

This paper argues that alternative heuristics, such as recency bias, play an important role in the expectations formation of economic agents operating under uncertainty. Based on this premise, the paper redefines the reference period used to calculate rainfall shocks. Existing literature use long-run climate normals to identify thresholds-30-year normals. While this has a reasonable scientific basis and appropriate for academic exercises. But unless agents that make real economic decisions based on such estimations have timely access, it would not reflect the decision-making process involved. This is especially true for rainfall forecasts in India. Although there have been significant improvements in the accuracy of forecasts, farmers have limited access to timely forecasts (Palit, 2025). Barriers to access include factors such as lack of trust, poor internet connectivity, and the absence of infrastructure to convey forecasts into actionable local information. Digital technology has ameliorated a lot of these problems, but unless it is adopted at a large scale, alternative heuristics will continue to influence farmers' expectations about future weather and subsequent agricultural decisions. To account for the incomplete information available to farmers at the time of decision-making, we use a rolling 3-year window as the reference period to define rainfall shocks. We follow earlier research by Jayachandran (2006) Mahajan (2017) and Kaur (2019) in using the deviations from the 20th and 80th percentiles of the rolling 3-year rainfall distribution for each district-year to define negative and positive rainfall shocks, respectively. To ensure temporal compatibility of the variables in our estimation model, we estimate the effect of rainfall shocks across the agricultural year (both sowing and harvest season) on annual district-level male and female field labor wages. There are several key takeaways from this analysis. First, negative shocks during the sowing season and positive shocks during the harvest season have the most salient impact on field labor wages. Second, these negative effects are amplified in districts with large areas under rice cultivation and with more irrigated area. The latter highlights the unintended role that irrigation infrastructure might have on labor market outcomes during rainfall shocks. Despite acting as a buffer during negative shocks, irrigation infrastructure can exacerbate downward pressure on wages by intensifying labor supply during adverse shocks. Third, access to markets might dampen some of these negative effects. We find some evidence that this may be operating through the price-wage pathway. There is a positive association between the number of agricultural markets and the market price of rice and wheat in a district. The higher prices, especially for rice, are also positively associated with higher wages for hired labor. This paper contributes to the growing literature on adaptation to weather shocks. Using a combination of district and household level analysis, we show that when farmers rely on alternative heuristics to form expectations about future rainfall patterns, the negative effects of shocks on wages can be intensified by irrigation and rice acreage, but ameliorated by higher competition in the market for agricultural produce.

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APPENDIX

Additional Materials and Supplementary Information

A IMD Forecasts and Rainfall Shocks

In this section we compare how the rainfall shock defined in this paper differs from the forecasts of rainfall published by the Indian Meteorological Department (IMD). This comparison is necessary as several economic indicators and advance estimates for the agricultural economy rely on the IMD forecasts (Gilmont et al., 2018; Iyer & Sen Gupta, 2019; Rosenzweig & Udry, 2014).

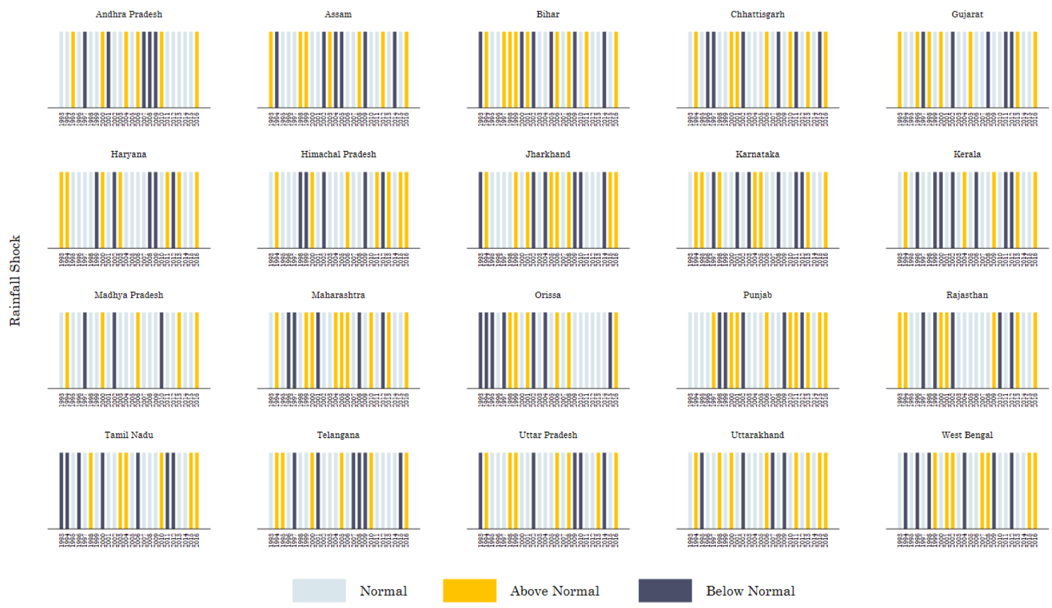
We compare the distribution of rainfall shocks across India, as defined in this paper, with the departure of rainfall estimated by the Indian Meteorological Department (IMD). Departure from normal rainfall is calculated by the IMD using the reference period 1951-2000 to define the normals for each region. For more recent data, post 2018, the reference period was changed to 1961-2010. Since we analyze the time period between 1993 and 2017 in this study, we use the earlier reference period (1951-2000) to calculate the departure from normal rainfall. IMD defines departure (in %) as:

$$\text{Depature}(\%) = \frac{(\text{Actual Rainfall - Normal Rainfall})}{\text{Normal Rainfall}} \times 100$$

If *Departure* is greater than 20% then it is considered excess and if it is greater than 60% large excess (LE). In figure 7 above normal rainfall captures the departures in observed rainfall greater than 20% of the historical normal. Negative shocks (or deficient rainfall according to IMD) are identified as departures that are greater than -20%. All rainfall departures between -19% and 19% are considered as normal rainfall. In panel a of figure 7, we report the type of rainfall shock for each state-year pair. In panel b of figure 7, the IMD departure from 'normal' rainfall for each state-year pair is reported.

Figure 7: Rainfall Shocks and Departure from Normal

(a) Rainfall shocks



(b) Departure from ‘normal’

Because the IMD data is collected by the sub-divisional offices of the IMD located across the states, direct comparison of the forecasts by the sub-divisional offices with the district-level rainfall shock variable defined in this paper is not feasible. We aggregate the rainfall shock and departure from the 'normal' variable to the state level to facilitate a comparison of the two.

For the rainfall shock variable, which was initially defined for each district-year pair, we use the share of districts in a state to identify whether a state experienced positive/negative shocks or normal rainfall in a year. A year is defined as a positive shock year if the share of districts experiencing

$$\begin{aligned} \text{positive shock}_t > \text{negative shock}_t, \\ \text{and} \\ \text{positive shock}_t + \text{negative shock}_t > \text{normal rain}_t \\ \forall t \in 1993, 1994, ..., 2017 \end{aligned}$$

Similarly, a year is defined as experiencing 'normal' rainfall if the share of districts experiencing normal rainfall $> 50\%$: Finally, a year is considered to be experiencing a negative shock if they experienced neither positive shocks nor normal rainfall. We conduct a similar exercise to calculate the state-level aggregates for the IMD departure from 'normal' variable. The only difference is that for the IMD variable, we aggregate over the sub-divisions to arrive at our state-level aggregates.

From the two panels in figure 7 we can notice a stark difference in how the years are classified into the different categories. One clear observation is the presence of a lot more 'normal' rainfall years when rainfall shocks are defined using the rolling 3-year historical rainfall distribution. For the IMD forecasts that use a much longer (1951-2000) reference period, the years are mostly classified as either negative or positive. More specifically, 29%($\simeq 160$ observations) of the state-year pairs in panel a experienced a positive shock while 20% experienced negative shocks. The corresponding figures for the IMD departure from normal are 34% and 56%, respectively. Farmers are constantly adapting to changing situations, and therefore, we argue that using a more recent and rolling reference period might better reflect actual decision-making processes.

B Household Level Analysis

Agricultural households in developing economies occupy a unique position in labor markets as they simultaneously function as both producers and consumers, creating a complex web of interdependent decisions that traditional single-equation models fail to capture adequately. Within the agricultural household framework established by Singh et al. (1986), these households make joint production and consumption decisions where family members optimize their time allocation between on-farm work, off-farm labor supply, and leisure, while simultaneously determining agricultural output levels and hired labor demand for their farming operations. This integrated decision-making process fundamentally differs from pure consumer households or firms because agricultural households experience direct profit effects from price and productivity changes—variations in agricultural conditions affect both farm profitability (influencing consumption capacity and labor demand) and household labor supply decisions through changes in the shadow value of time. The simultaneity arises because changes in agricultural productivity or rainfall patterns alter farm profits, which in turn affect household income and consumption patterns, while simultaneously modifying the marginal productivity of both family and hired labor, creating feedback effects between production decisions and labor market participation. Under the recursive property of the agricultural household model, production decisions (including hired labor demand) are made by equating the marginal revenue product of labor to the market wage, while labor supply decisions respond to changes in full income (including both wage income and farm profits), creating a system where shocks to agricultural productivity propagate through both production and consumption channels. Given that rainfall shocks affect farm profitability, alter the marginal productivity of labor inputs, and modify household income through the profit effect, estimating the effects of weather variability requires a simultaneous equations approach that accounts for the interconnected nature of production and consumption decisions within the theoretical framework of the agricultural household model.

Therefore, to understand the underlying dynamics of the labor-leisure tradeoff of agricultural households, we estimate a system of simultaneous equations. This allows us to model the joint determination of agricultural labor supply and hired wages in response to rainfall shocks:

$$\ln(\text{Labor Supply})_{it} = \beta_0 + \beta_1 \ln(\text{Hired Wage})_{it} + \boldsymbol{X}_{it}^{L}\boldsymbol{\beta} + \boldsymbol{R}_{it}\boldsymbol{\beta}^{R} + \varepsilon_{1it} \tag{11a}$$

$$\ln(\text{Hired Wage})_{it} = \gamma_0 + \gamma_1 \ln(\text{Labor Hours})_{it} + \boldsymbol{X}_{it}^{W}\boldsymbol{\gamma} + \boldsymbol{R}_{it}\boldsymbol{\gamma}^{R} + \varepsilon_{2it} \tag{11b}$$

where, $\boldsymbol{X}_{it}^{L}$ is a vector of household-level covariates that influence the labor supply decision, such as the number of adult household members, size of operational holding, outstanding household debt, and social identifiers such as caste and religion. Similarly, $\boldsymbol{X}_{it}^{W}$ is the vector of production attributes that might influence wages of labor hired by the households. These include the amount of expenditure on fertilizers and farming equipments, and the size of operational holding.

The rainfall shock variables include the main and interaction effects of seasonal rainfall shocks as defined earlier in Section 2.3, i.e:

$$\begin{aligned}\boldsymbol{R}_{it} = [&\text{Positive Sowing}_{it}, \text{Positive Harvest}_{it}, \text{Negative Sowing}_{it}, \text{Negative Harvest}_{it},\\ &(\text{Positive Sowing} \times \text{Positive Harvest})_{it}, (\text{Negative Sowing} \times \text{Negative Harvest})_{it},\\ &(\text{Positive Sowing} \times \text{Negative Harvest})_{it}, (\text{Negative Sowing} \times \text{Positive Harvest})_{it}]\end{aligned}$$

We use household-level data on farm households from the two waves of the India Household Development Survey (IHDS)- I (2004-05) and II (2011-12) (Desai & Vanneman, 2015; Desai et al., 2008). To capture the effect of contemporaneous rainfall shocks on household decision-making, we merge the household-level data with the district-level rainfall shock data from TCI-ICRISAT that we have used in the main analysis of this paper. We confine our analysis to only the two years during which the survey was conducted. So, rainfall data is used only for 2004 and 2011 from the TCI-ICRISAT database. Given the changes in district boundaries and nomenclatures, we manually combed through the districts in the two separate databases to identify the districts that were common across datasets. Finally, we were able to merge 350 districts successfully. After further data pre-processing, our final estimation sample consists of 2140 households from 182 districts.

We employ a three-stage least squares framework to estimate the effect of rainfall shocks on household labor supply and their impact on hired wages (Zellner & Theil, 1962). In the above framework, wages and labor supply are endogenous variables. The 3SLS procedure involves developing instrumented values for all the endogenous variables (step 1). This is done by predicting the values from a regression of each endogenous variable on all exogenous variables in the system. Subsequently, we obtain a consistent estimate for the covariance matrix of the equation disturbances from the residuals of the 2SLS estimation of each structural equation (step 2). Finally, we perform a generalized least square (GLS) estimation using the covariance matrix estimated in the second step, and the predicted values of the endogenous variables (obtained in step 1) in place of the endogenous variables on the right-hand side of the system of equations (step 3). The reg3 command in STATA19 was used to perform this 3SLS procedure. The system is identified through exclusion restrictions. In the labor supply equation, the excluded instruments are production-specific variables (*Fertilizers*, *Equipment*) that affect hired wage determination through productivity but not individual labor supply decisions directly. Similarly, in the wage equation, the excluded instruments are household attributes such as number of adult members, outstanding debt and caste and religious affiliation that affect labor supply but not wage determination

Table 8: 3SLS Estimation Results: Labor Supply and Hired Wage

Variable	**Labor Supply**	**Hired Wage**
Endogenous Variables		
Hired Wage (log)	0.011 (0.022)	
Labor Hours (log)		0.246** (0.123)
Household & Production		
Adult Members (log)	0.356*** (0.028)	
Household Debt (log)	-0.008 (0.009)	
Land Holding (log)	0.002 (0.009)	0.018 (0.015)
Fertilizers (log)		0.408*** (0.028)
Equipment (log)		0.298*** (0.028)
Social Groups $		
OBC	-0.010 (0.040)	
Dalit	0.025 (0.042)	
Adivasi	0.114** (0.051)	
Muslim	-0.061 (0.052)	
Christian, Sikh or Jain	-0.232 (0.206)	
Rainfall Main Effects		
Positive Sowing	-0.157*** (0.058)	-0.003 (0.111)
Positive Harvest	-0.218*** (0.077)	0.124 (0.164)
Negative Sowing	-0.044 (0.051)	0.069 (0.108)
Negative Harvest	-0.029 (0.048)	0.125 (0.094)
Rainfall Interactions		
Pos. Sowing × Pos. Harvest	0.407*** (0.138)	-0.162 (0.264)
Neg. Sowing × Neg. Harvest	0.023 (0.071)	-0.171 (0.149)
Pos. Sowing × Neg. Harvest	0.008 (0.072)	-0.315** (0.132)
Neg. Sowing × Pos. Harvest	0.313* (0.174)	-0.638** (0.268)
Constant	26.228*** (9.576)	140.763*** (16.613)
Observations	2140	2140
R-squared	0.190	0.424
Region F.E.	✓	✓
Time trend	✓	✓
Districts	182	182

Notes: * p<0.10, ** p<0.05, *** p<0.01. $ Reference category for social groups is forward caste. Standard errors clustered at the village or Primary Sampling Unit (PSU) level are in parentheses. Estimates are based on matched household data from IHDS I (2004-05) and II (2011-12) and TCI-ICRISAT weather data.

directly.

In Table 8 we present the results of our 3SLS model. First, examining the labor supply equation, we see that total household labor supply is positively associated with the number of adult household members. There is a negative association between total outstanding household debt and labor supply, but this effect is not statistically significant. We also see that relative to 'forward caste' households, 'adivasi' households are more likely to supply agricultural labor. Finally, we see that positive shocks during the sowing and harvest season decrease labor supply, relative to districts with normal rainfall- indicating that perhaps the income effect dominates the labor-leisure trade-off in household labor supply decisions. Negative shocks also result in reduced labor supply but this would operate through the dominance of the substitution effect- leisure is relatively cheaper now because of lower opportunity cost.

But when we look at the interaction effects, we find a strong positive association between labor supply and rainfall shocks in districts that experience positive rainfall shocks during sowing *and* harvest seasons, relative to districts experiencing normal rainfall. This indicates that when households experience positive rainfall shocks during both sowing and harvest periods, they supply significantly more agricultural labor than would be expected from simply adding the individual effects. A similar effect is observed when households face negative shocks in the sowing season and positive shocks in the harvest season.

For hired wages, the interaction effects show a different pattern. The Positive Sowing $\times$ Negative Harvest and Negative Sowing $\times$ Positive Harvest interactions are both negative and statistically significant (-0.315 and -0.638, respectively). This suggests that when rainfall shocks are discordant across seasons—good sowing with bad harvest or bad sowing with good harvest—wages fall more than would be expected from considering main effects separately. In economic terms, these negative and significant interaction effects highlight situations where unfavorable conditions at any stage disrupt the labor market, possibly lowering the demand for hired labor or increasing labor supply from distressed households, thus depressing wages. But these interaction effects do not represent the total effect of experiencing both shocks (main effect + interaction effects). We report these estimates in section 6. The discussion of the mechanisms that drive household labor supply decisions (Section 5.1) is based on estimates of the agricultural household model discussed here.

C Historical climate normals

Table 9: Impact of Rainfall Shocks on Wages by Gender

	Male (1)	**Female** (2)
Irrigation (log)	0.003	-0.000
	(0.016)	(0.015)
Rice area (log)	-0.012	0.020
	(0.023)	(0.025)
Fertiliser (log)	-0.017	-0.025
	(0.029)	(0.035)
Rainfed Rice System (Yes = 1)	0.026	-0.034
	(0.032)	(0.023)
Positive sowing season shock	-0.006	-0.014
	(0.014)	(0.016)
Positive harvest season shock	0.033**	0.033**
	(0.015)	(0.017)
Negative sowing season shock	-0.000	0.023
	(0.013)	(0.016)
Negative harvest season shock	0.001	0.011
	(0.016)	(0.018)
Positive Sowing × Positive Harvest	0.022	0.045
	(0.027)	(0.035)
Negative Sowing × Negative Harvest	0.025	-0.007
	(0.028)	(0.033)
Positive Sowing × Negative Harvest	-0.029	-0.035
	(0.033)	(0.030)
Negative Sowing × Positive Harvest	-0.058*	-0.068*
	(0.029)	(0.037)
Observations	2,490	1,506
Districts	230	170
Mean Wage (Rs/day)	146.2	75.7
R-squared	0.946	0.934
Within R-squared	0.008	0.014
Year FE	✓	✓
District FE	✓	✓

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses.

This table reports the effect of rainfall shocks on male and female field labor wages. Rainfall shock is defined as deviations from the previous 30-year rainfall distribution for each district-year pair. We use apportioned data from 313 districts between 1966-2017 from the TCI-ICRISAT District Level Database ("ICRISAT-District Level Data", n.d.). The estimation sample, however, contains data from 1996 to 2017 to ensure comparison with our baseline results. We follow the em-

Table 10: Total effect of rainfall shocks on wages

Shock	Female Coeff.	Female Effect (Rs/day)	Male Coeff.	Male Effect (Rs/day)
Negative Sowing × Negative Harvest	0.028	2.094	0.026	3.788
Negative Sowing × Positive Harvest	-0.012	-0.875	-0.025	-3.723
Positive Sowing × Negative Harvest	-0.038	-2.863	-0.034	-5.043
Positive Sowing × Positive Harvest	0.065**	4.903	0.048**	7.058

Note: * p<0.10, ** p<0.05, *** p<0.01. Effects calculated using the model coefficients from table 9. The effect columns show change in Rs/day which was estimated based on the sample mean of the nominal wages for men and women field labor. Given the log-linear model specification in equation 6, the effect is calculated by multiplying the coefficient of the total effect by the mean wage.

pirical strategy used in estimating our baseline model 6. Our hypothesis was that the joint effects would not be significant because farmers are more sensitive to recent rainfall experiences. Table 10 reports the estimates of the total effect of rainfall shocks across the two phases of the agricultural cycle. We observe that the effects are not statistically significant for most shock combinations. However, we find that the effects are statistically significant for the Positive Sowing × Positive Harvest shock combination. In our baseline model, this combination of shocks did not have a statistically significant effect on field labor wages. From this we can argue that when realized rainfall deviates from the long-run climate normal in a district, the effects on wages cannot be distinguished from zero. But, in the case of positive shocks in both sowing and harvest season, we see that there is an increase in wages for both male and female field labor. Moreover, the effect is larger for female field labor (6.5 percent comaped to 4.8 percent).

D Testing recency bias

We have been arguing that farmers' perceptions about weather shocks are influenced by their historical experiences. To justify this, we follow ongoing work by Nutsugah (2025) to empirically test this assumption. We use the apportioned district-level database of TCI-ICRISAT ("ICRISAT-District Level Data", n.d.) construct indicators for the lagged rainfall shock variables using the 30-year climate normal definition used in section C. Specifically, we construct two types of lagged variables. One, recent lags that range from 1 to 5 years. Second, we construct more aggregate counts of shocks experienced between 6 to 10 years, 11 to 15 years and 16 to 20 years. The latter reflects the occurrence of shocks over a relatively longer history. The idea, following Nutsugah (2025), is to check if at least one of the recent lags is statistically significant, but not the historical aggregate shocks. Using a district-level panel data spanning 1971-2017, we estimate the following model:

$$\begin{aligned}
\text{Wage}^{g}_{i,t} = \beta_0 &+ \beta_1 \text{Irrigation}_{i,t} + \beta_2 \ln(\text{RiceArea}_{i,t}) + \beta_3 \text{Fertiliser}_{i,t} \\
&+ \beta_4 \text{RainfedRiceSystem}_{i,t} + \beta_5 \text{Shock}_{i,t} \\
&+ \beta_6 \ln(\text{RiceYield}_{i,t-1}) + \sum_{j=1}^{5} \gamma_j \text{Shock}_{i,t-j} \\
&+ \delta_1 \text{ShockCount}^{6-10}_{i,t} + \delta_2 \text{ShockCount}^{11-15}_{i,t} \\
&+ \delta_3 \text{ShockCount}^{16-20}_{i,t} + \alpha_i + \mu_t + \epsilon_{i,t} \qquad (12)
\end{aligned}$$

where, $\text{Wage}^{g}_{i,t}$ refers to the natural logarithm of the field labor wages in district i and year t for gender $g \in \{Male, Female\}$. Our estimation sample for male and female wages consists of 273 and 219 districts, respectively. The model estimates are reported in table 11.

In table 11, we present the dynamic effects of district-level rainfall shocks on male and female field labor wages. Although we are unable to find strong evidence of a recency bias as suggested by Nutsugah (2025), the results are promising and provide a reasonable basis for using the 3-year reference period in our main analysis. We find that contemporary positive harvest shocks significantly raise both male and female field labor wages in the same year, while negative harvest shocks reduce wages immediately for both genders. Beyond the contemporaneous impact, the one- and two-year lags of positive shocks exhibit the largest and most precisely estimated coefficients, whereas coefficients for lags three to five decline in magnitude and lose significance. Medium-term windows (6–10 and 11–15 years) show no consistent wage effects for men and only a marginal negative effect of negative harvest shocks six to ten years prior for women. Although some very

Table 11: Recency Effects of Rainfall Shocks on Field Labor Wages

	Male wages				Female wages			
	(1) PosSow	(2) PosHarv	(3) NegSow	(4) NegHarv	(5) PosSow	(6) PosHarv	(7) NegSow	(8) NegHarv
Irrigation	0.010	0.008	0.009	0.010	0.000	-0.003	-0.002	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
ln(RiceArea)	-0.072***	-0.067***	-0.068***	-0.069***	-0.057***	-0.054**	-0.054**	-0.051**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)	(0.021)
Fertiliser	-0.015	-0.016	-0.017	-0.013	-0.048***	-0.047***	-0.048***	-0.044**
	(0.021)	(0.020)	(0.020)	(0.021)	(0.018)	(0.018)	(0.018)	(0.018)
Rainfed system	0.032	0.031	0.038	0.040	-0.038*	-0.043*	-0.041*	-0.029
	(0.026)	(0.025)	(0.025)	(0.026)	(0.023)	(0.022)	(0.023)	(0.023)
Contemp. shock	0.017	0.048***	-0.008	-0.036**	0.009	0.053**	0.004	-0.036**
	(0.014)	(0.016)	(0.012)	(0.014)	(0.018)	(0.023)	(0.014)	(0.016)
ln(RiceYield$_{t-1}$)	0.010	0.005	0.007	0.009	-0.021	-0.023	-0.024	-0.022
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.017)	(0.017)	(0.017)
1-year lag	0.003	0.044***	0.004	0.016	0.026	0.040*	0.011	-0.004
	(0.015)	(0.017)	(0.013)	(0.014)	(0.020)	(0.023)	(0.015)	(0.016)
2-year lag	0.036**	0.031**	-0.019	-0.008	0.049**	0.018	-0.009	-0.011
	(0.017)	(0.014)	(0.013)	(0.014)	(0.020)	(0.019)	(0.016)	(0.016)
3-year lag	0.008	0.031**	-0.016	-0.005	0.037*	0.011	-0.005	-0.024
	(0.018)	(0.014)	(0.014)	(0.016)	(0.021)	(0.020)	(0.015)	(0.017)
4-year lag	0.005	0.030**	-0.033**	-0.012	0.030	-0.017	-0.029*	-0.017
	(0.016)	(0.015)	(0.015)	(0.017)	(0.020)	(0.018)	(0.016)	(0.018)
5-year lag	-0.013	-0.007	-0.028**	-0.004	-0.025	-0.045**	0.007	-0.008
	(0.017)	(0.016)	(0.014)	(0.016)	(0.020)	(0.017)	(0.016)	(0.020)
Total (6–10 yr)	-0.003	0.013	-0.021	-0.029*	0.000	-0.011	-0.021	-0.047**
	(0.016)	(0.015)	(0.013)	(0.015)	(0.014)	(0.015)	(0.013)	(0.021)
Total (11–15 yr)	-0.028	-0.011	0.016	-0.014	0.004	-0.025	0.012	-0.039
	(0.019)	(0.018)	(0.017)	(0.019)	(0.021)	(0.022)	(0.020)	(0.031)
Total (16–20 yr)	-0.012	-0.012	-0.004	-0.046*	-0.098***	-0.006	0.103**	-0.084*
	(0.023)	(0.023)	(0.026)	(0.026)	(0.031)	(0.042)	(0.046)	(0.043)
_cons	3.385***	3.401***	3.427***	3.372***	3.834***	3.843***	3.855***	3.800***
	(0.238)	(0.235)	(0.235)	(0.239)	(0.211)	(0.207)	(0.208)	(0.209)
Observations	6776	6776	6776	6776	3830	3830	3830	3830
R^2	0.979	0.980	0.979	0.979	0.965	0.965	0.965	0.965
Districts	273	273	273	273	219	219	219	219
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses. The table presents estimates of equation 12 for each of the four shock types (positive sowing, negative sowing, positive harvest, negative harvest), with separate regressions for male and female field labor wages. Columns report the coefficients of several control variables, the rainfall shock indicator, and its 1-, 2-, 3-, 4-, and 5-year lags. In addition, we include variables measuring the total frequency of each shock over three historical intervals (6–10, 11–15, and 16–20 years prior). Each specification, therefore, isolates the dynamic impact of a single shock type and captures both its short- and longer-run occurrences.

long-term windows (16–20 years) display isolated significant effects—particularly a large negative legacy from positive sowing shocks on female wages and a positive legacy from early harvest shocks—these long-run structural legacies differ from the short-run labor-market responses. Overall, the evidence confirms the presence of some recency bias: rainfall shocks exert their primary influence on field labor wages within the first two years, with negligible medium-term effects.

E Sensitivity to distribution of monthly rainfall

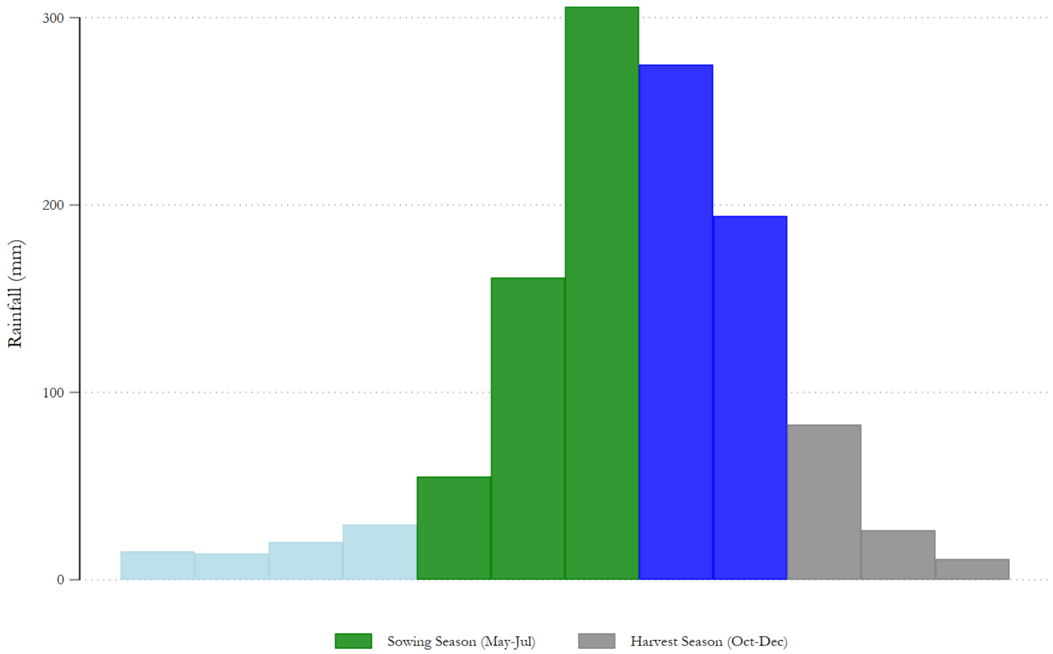
In our main analysis we estimated the effect of rainfall shocks experienced across two major agricultural phases of the *Kharif* (monsoon) season- sowing and harvest. Sowing and harvest months were identified using the crop calendar (M. o. A. a. F. W. Govt. of India, 2021). The months of May, June and July were identified as sowing months, whereas October, November and December are the harvest months. Our analysis defined rainfall shocks as deviations from the previous 3-year rainfall distribution in each district-year pair over these two seasons separately. But, rainfall shocks could be occurring maybe in a few days or in one particular month of the entire season. The histogram shows the distribution of average rainfall across the 12 months (see figure 8). In this section, we provide a sensitivity analysis by defining rainfall shocks explicitly for each of the months.

From figure 8 we can see that the distribution of rainfall is heterogeneous even within the sowing and harvest months. For instance, rainfall is concentrated in July and October in the sowing and harvest months, respectively. We will conduct a more disaggregated analysis using rainfall shocks for each month. Moreover, we will also check whether rainfall shocks in August and September (dark blue bars) affect wages. Using the unapportioned district-level data, we construct rainfall shock indicators for each month. Here, we use the rainfall shock definition used in our main analysis- based on the 3-year rolling window reference period. We estimate the following model:

$$\begin{aligned}
Wage^{g}_{i,t} = {} & \beta_0 + \beta_1\,\mathrm{Irrigation}_{i,t} + \beta_2\,\ln\big(\mathrm{RiceArea}_{i,t}\big) + \beta_3\,\mathrm{Fertiliser}_{i,t} \\
& + \beta_4\,\mathrm{RainfedRiceSystem}_{i,t} \\
& + \sum_{m=\mathrm{Jan}}^{\mathrm{Dec}} \Big[\gamma^{+}_{m}\,\mathrm{positive}_{m,i,t} + \gamma^{-}_{m}\,\mathrm{negative}_{m,i,t}\Big] \\
& + \alpha_i + \mu_t + \varepsilon_{i,t} \qquad (13)
\end{aligned}$$

We follow the same notations as used in earlier models. $\mathrm{positive}_{m,i,t}$ refers to the indicator for the positive shock in month m year t and district i, and γ^{+}_{m} is the

Figure 8: Average monthly rainfall distribution

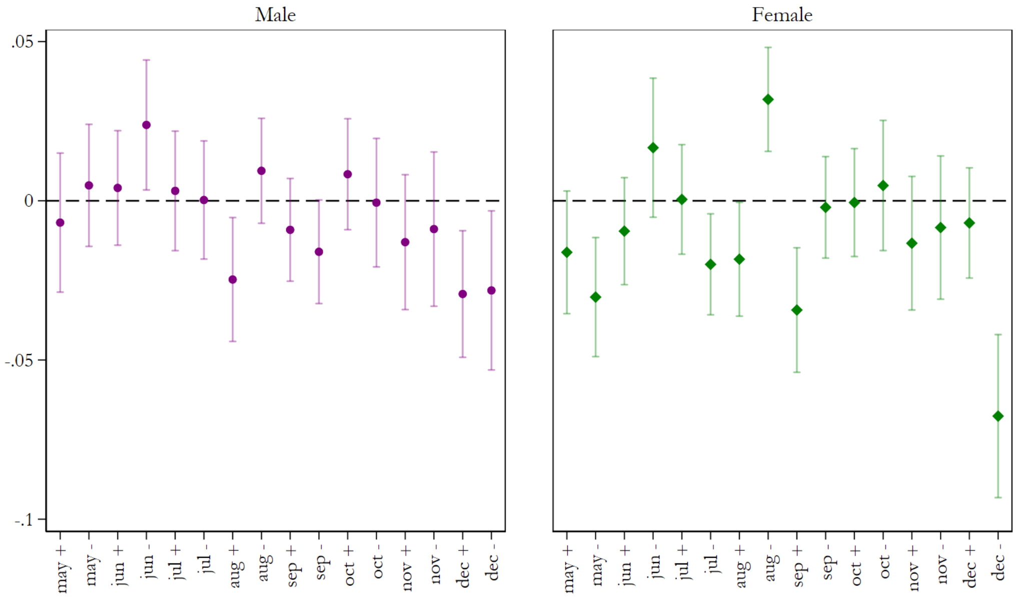


Note: The figure reports the average monthly rainfall distribution across 586 districts between 1990-2017. We highlight the sowing season for Kharif rice in green and the harvest season in gray. The months are identified using the ICAR crop calendar and reflect the nationwide distribution of sowing and harvest months. They may vary slightly across states.

associated coefficient. Similarly, negative$_{m,i,t}$ is the indicator for negative shock in month m year t and district i, and γ_m^- is the associated coefficient.

In figure 9 the estimates of γ_m^+ and γ_m^- from equation 13 are depicted for male and female field labor wages. We find that male wages respond significantly to June negative shocks, August positive shocks, and both positive and negative shocks in December, indicating sensitivity at sowing onset, peak monsoon, and end-of-harvest. This follows our main findings in section 3, where we see that male wages are affected by the combination of a negative sowing $\times$ positive harvest shock. Here, too, we see that a negative shock in the month of June has a positive effect on wages, whereas a positive shock in December depresses the wages. Female wages are significantly depressed by negative shocks in May, July, August, and December, and boosted by a September positive shock, reflecting women's greater

Figure 9: Monthly shock effects



Note: The figure reports estimated coefficients of equation 13 for male and female field labor, respectively. We report the results of positive and negative shocks for May to December. Each model includes various controls, such as irrigated area, rainfed rice system, fertiliser use, district, and year fixed effects. All errors are clustered at the district level.

vulnerability to month-specific rainfall deviations throughout the Kharif season. These results provide evidence that the effects of seasonal shocks that we identified in our main analysis are driven by shocks in June, August and December for male field labor wages; and May, July, August, and December for female field labor wages.