



# Rainfall Shocks and Rural Employment in India: Evidence from State-Level Secondary Data

Amar Tukaram Ther

Research Scholar, Department of Economics

Dnyanprakash Arts College, Pinjar, Dist. Akola. S.G.B.A. University, Amravati

Email- amarthert@gmail.com

**Abstract:** Rainfall variability can affect rural labour markets through agricultural production, labour demand, household income and occupational adjustment. This study examines the association between rainfall shocks and rural employment across Indian states using secondary data for 2023. The analysis combines state-level rainfall departures from normal reported by the India Meteorological Department (IMD) with rural Worker Population Ratio (WPR) estimates for persons aged 15 years and above under usual status from the Periodic Labour Force Survey (PLFS) 2023–24. The empirical analysis covers 28 states and estimates a cross-sectional ordinary least squares model with heteroskedasticity-robust standard errors. The estimated coefficient on rainfall departure is positive but statistically insignificant: a one-percentage-point increase in rainfall departure is associated with an estimated 0.080 percentage-point increase in rural WPR, with a robust standard error of 0.079 and a p-value of 0.311. The model explains approximately 2.75 per cent of the cross-state variation in rural WPR. The results therefore do not provide statistically significant evidence of a linear relationship between the 2023 rainfall shock measure and rural employment across states. This finding should not be interpreted as evidence that rainfall is economically irrelevant. State-level employment responses may be mediated by irrigation, agricultural diversification, migration, non-farm employment, public employment programmes and differences in the timing and geographical distribution of rainfall. The study highlights the limitations of cross-sectional state-level analysis and establishes a basis for future panel and district-level research using repeated PLFS and meteorological observations.

**Keywords:** rainfall shocks; rural employment; Worker Population Ratio; PLFS; monsoon; agricultural labour markets; India; climate variability

**JEL Classification:** J21; O12; O54; O18

## 1. INTRODUCTION

Weather variability represents an important source of economic uncertainty for rural households in developing economies. In India, rainfall is particularly relevant because agricultural production and rural livelihoods remain influenced by the timing, intensity and geographical distribution of precipitation. Rainfall conditions can affect crop production, agricultural labour demand, farm income and the availability of employment opportunities. Consequently, weather shocks may influence labour-market outcomes even when their effects are not immediately observable in aggregate economic indicators.

The relationship between rainfall and rural employment is theoretically ambiguous. Above-normal rainfall may improve agricultural conditions and increase demand for labour during agricultural operations. In contrast, deficient rainfall can reduce agricultural activity and labour requirements. Excessive rainfall may also have adverse consequences when it causes flooding, waterlogging or crop damage. The effect of rainfall on employment therefore depends on the magnitude and direction of the shock as well as the capacity of rural households and labour markets to adjust.



Labour-market adjustment can occur through several channels. Workers may move between agricultural and non-agricultural activities, migrate temporarily or permanently, increase self-employment or seek employment through public works programmes. Irrigation can also reduce dependence on rainfall, while diversified state economies may provide alternative employment opportunities. These mechanisms imply that the relationship between rainfall and aggregate rural employment cannot be assumed to be one-to-one.

The Periodic Labour Force Survey (PLFS), conducted by the Ministry of Statistics and Programme Implementation (MoSPI), provides nationally comparable labour-market estimates. The annual PLFS reports provide estimates of the Worker Population Ratio (WPR), Labour Force Participation Rate and Unemployment Rate by sector, sex, age and state. The 2023–24 PLFS covers July 2023 to June 2024. For persons aged 15 years and above, rural WPR under usual status (principal status plus subsidiary status) was 62.1 per cent at the all-India level.

The India Meteorological Department (IMD) publishes annual rainfall statistics containing state-wise observed rainfall and percentage departures from normal. The 2023 report provides state-level seasonal and annual rainfall statistics, allowing the construction of a state-level rainfall-shock measure.

Against this background, the present study asks:

### **Is variation in rainfall from normal conditions associated with rural employment across Indian states?**

The study contributes to the literature in three ways. First, it combines two official Indian government datasets PLFS and IMD to examine the relationship between environmental conditions and labour-market outcomes. Second, it focuses on rural WPR among persons aged 15 years and above, thereby capturing broad rural employment rather than a single occupation. Third, it provides an empirical benchmark for the relationship using a common cross-sectional year before moving to more demanding panel and district-level designs.

The study deliberately uses the term association rather than causal effect. Because the analysis is cross-sectional, differences between states that are correlated with both rainfall and employment cannot be completely eliminated. The results should therefore be interpreted as descriptive econometric evidence rather than causal estimates.

## **2. THEORETICAL FRAMEWORK**

The potential relationship between rainfall and rural employment can be understood through agricultural labour demand.

Let agricultural output in state  $i$  be represented by:

$$Y_i = F(A_i, L_i, R_i, K_i),$$

where  $A_i$  represents land and fixed agricultural characteristics,  $L_i$  labour,  $R_i$  rainfall and  $K_i$  other productive inputs.

Rainfall can influence agricultural productivity and the timing of agricultural activities. When rainfall conditions are favourable, agricultural production may increase, potentially raising demand for labour for cultivation and harvesting. A rainfall deficit may reduce agricultural activity and employment opportunities.

However, excessive rainfall can also reduce agricultural activity through crop damage, flooding and disruption. Consequently, the rainfall-employment relationship may be nonlinear.

The aggregate rural WPR reflects household responses to these conditions. Workers can shift into non-farm employment, construction, services, self-employment or migration. Public employment programmes may also influence labour-market responses. Therefore, the observed state-level relationship represents the net outcome of several channels.

The theoretical framework leads to the following empirical expectation:

$$\text{Rainfall Shock}_i \rightarrow \text{Agricultural Conditions}_i \rightarrow \text{Labour Demand}_i \rightarrow \text{Rural Employment}_i.$$

The sign and magnitude of the final relationship remain empirical questions.

## **3. LITERATURE REVIEW**

Research on weather shocks and rural labour markets provides several mechanisms relevant to India.



Rosenzweig and Udry (2014) show that rainfall forecasts and weather conditions can influence agricultural decisions, wages and labour-market outcomes over the agricultural production cycle. Their findings demonstrate that rainfall can generate economically meaningful variation in agricultural activity.

Kaur (2019) examines rural labour markets in India and documents substantial wage rigidity. Wage rigidity is relevant to rainfall shocks because temporary changes in labour demand may not be fully reflected in wages and may instead influence employment opportunities or labour-market rationing.

Jayachandran (2006) demonstrates how productivity shocks can affect rural wages in developing economies. Such evidence provides a theoretical basis for examining weather-related changes in labour demand.

Colmer (2021) provides evidence that environmental conditions can affect labour reallocation and industrial production in India. This is important because the response to weather shocks need not be restricted to agricultural employment.

More recent work has explicitly examined rainfall shocks and labour supply in India. Maitra et al. examine labour-supply responses to rainfall shocks using historical district-level rainfall and employment data, distinguishing positive and negative rainfall shocks. Taraz examines the relationship between India's public employment programme and agricultural risk, highlighting the importance of labour-market and income channels through which public works can interact with weather shocks.

The existing literature therefore suggests that weather conditions can influence rural labour markets, but the direction and magnitude of the relationship depend on agricultural dependence, labour mobility, non-farm opportunities and public policy.

The present study adds a recent state-level observation by combining PLFS 2023–24 employment information with IMD 2023 rainfall departures.

#### **4. OBJECTIVES OF THE STUDY**

The study has four objectives:

1. To examine the relationship between rainfall departures from normal and rural employment across Indian states.
2. To estimate the association between rainfall shocks and rural WPR among persons aged 15 years and above.
3. To assess whether rainfall variation explains cross-state differences in rural employment.
4. To identify methodological implications for future panel and district-level studies of rainfall and employment in India.

#### **5. DATA AND METHODOLOGY**

##### **5.1 Data Sources**

The study uses two principal secondary data sources.

##### **Periodic Labour Force Survey**

The dependent variable is rural WPR for persons aged 15 years and above under usual status (principal status plus subsidiary status), obtained from the PLFS 2023–24.

PLFS is the official national source for employment and unemployment statistics in India. The 2023–24 annual report covers the period July 2023 to June 2024.

##### **India Meteorological Department**

The principal explanatory variable is rainfall departure from normal for 2023. IMD's *Rainfall Statistics of India 2023* provides state-wise observed rainfall and percentage departure from normal.

IMD's rainfall information system also provides state, subdivision and district rainfall products and historical rainfall reports.



## 5.2 Sample

The empirical analysis covers 28 Indian states.

Union Territories are excluded because the objective is to compare states with broadly comparable state-level rural employment and rainfall observations.

The final sample contains:  $N = 28$  state-level observations.

## 5.3 Dependent Variable

The principal dependent variable is rural Worker Population Ratio:

$$WPR_i = \frac{\text{Employed rural population}_i}{\text{Rural population}_i} \times 100.$$

The analysis uses persons aged 15 years and above and usual status (ps+ss).

The use of usual status is appropriate because it captures both principal activity and subsidiary economic activity over the longer reference period used by PLFS.

## 5.4 Rainfall Shock

Rainfall departure from normal is defined as:

$$\text{RainShock}_i = \frac{\text{ActualRainfall}_i - \text{NormalRainfall}_i}{\text{NormalRainfall}_i} \times 100.$$

A positive value indicates above-normal rainfall and a negative value indicates below-normal rainfall.

The measure is obtained from IMD's state-wise rainfall statistics.

## 5.5 Econometric Model

The baseline cross-sectional specification is:

$$\text{RuralWPR}_i = \alpha + \beta \text{RainShock}_i + \epsilon_i.$$

The parameter of interest is  $\beta$ .

A positive coefficient would indicate that states experiencing relatively higher rainfall departures also exhibit higher rural WPR, while a negative coefficient would indicate the opposite association.

Because the analysis is cross-sectional, the model does not include state fixed effects or year fixed effects.

Heteroskedasticity-robust standard errors are used.

## 5.6 Identification and Interpretation

The model estimates an association rather than a causal effect.

States differ in agricultural structure, irrigation, industrialisation, demographic composition, education, migration, public employment and labour-market institutions. These characteristics may be correlated with both rainfall conditions and employment.

Therefore:

$$\beta \neq \text{necessarily a causal rainfall effect.}$$

The analysis should be interpreted as evidence regarding the cross-state statistical relationship between rainfall departures and rural employment in 2023.



## 6. RESULTS

### 6.1 Descriptive Evidence

The PLFS 2023–24 data indicate substantial variation in rural employment across Indian states. At the all-India level, rural WPR for persons aged 15 years and above was 62.1 per cent under usual status. The corresponding rural WPR was 78.1 per cent for men and 46.5 per cent for women.

The substantial difference between male and female WPR demonstrates that rural labour-market participation is heterogeneous by gender. This is relevant because rainfall shocks may affect household labour allocation differently across men and women.

IMD's 2023 rainfall statistics also demonstrate substantial spatial variation in rainfall across states. For example, the report records large differences in state-level southwest monsoon and annual rainfall, reflecting India's considerable climatic heterogeneity.

The coexistence of substantial variation in rainfall and rural employment provides a basis for testing whether the two variables are systematically related.

### 6.2 Regression Results

The baseline OLS regression produces the following result:

| Variable                           | Coefficient        | Robust SE     | p-value      |
|------------------------------------|--------------------|---------------|--------------|
| Rainfall departure from normal (%) | <b>0.0803</b>      | <b>0.0792</b> | <b>0.311</b> |
| Constant                           | Estimated in model | —             | —            |
| Observations                       | <b>28</b>          |               |              |
| $R^2$                              | <b>0.0275</b>      |               |              |
| Adjusted $R^2$                     | Negative/very low  |               |              |

The estimated coefficient on rainfall departure is **0.0803**.

In substantive terms, a one-percentage-point increase in rainfall departure from normal is associated with an estimated **0.080 percentage-point increase in rural WPR**, holding no additional state-level covariates constant because the specification is bivariate.

However, the robust p-value is **0.311**, which is above conventional 10, 5 and 1 per cent significance thresholds.

The estimated relationship is therefore **not statistically distinguishable from zero in this sample**.

The model's  $R^2$  is 0.0275, indicating that rainfall departure alone explains approximately **2.75 per cent** of the cross-state variation in rural WPR.

### 6.3 Interpretation

The positive coefficient is consistent with the theoretical possibility that favourable rainfall conditions can support agricultural labour demand. However, the lack of statistical significance means that the evidence does not establish a systematic linear relationship across the 28 states in 2023.

The low explanatory power further indicates that rainfall departure alone cannot explain most of the cross-state variation in rural employment.

This result is economically plausible. Rural employment is influenced by many factors beyond rainfall, including irrigation, agricultural productivity, industrialisation, non-farm employment, migration, education, demographics and government employment programmes.

The result should therefore not be interpreted as evidence that rainfall has no effect on employment. Instead, it indicates that a simple state-level cross-sectional rainfall measure does not provide statistically strong evidence of a linear employment relationship for the 2023 observation.



## 7. DISCUSSION

The empirical result provides a useful but limited benchmark.

The positive coefficient is consistent with a conventional agricultural labour-demand mechanism. Better rainfall conditions may increase agricultural activity and labour requirements. However, several mechanisms may weaken the aggregate relationship.

First, irrigation reduces dependence on contemporaneous rainfall. States with extensive irrigation may maintain agricultural activity even when rainfall is below normal.

Second, rural economies are increasingly diversified. Workers may shift between agriculture, construction, manufacturing and services.

Third, migration can redistribute labour geographically. Workers may respond to local agricultural conditions by moving to other locations.

Fourth, public employment programmes can affect labour-market adjustment. MGNREGA can provide employment opportunities when agricultural employment is weak.

Fifth, the timing of rainfall matters. An annual rainfall departure may conceal whether rainfall occurred during critical agricultural periods. Two states with identical annual departures could experience very different agricultural consequences if rainfall is distributed differently across the agricultural season.

These mechanisms suggest that rainfall departure should not be treated as a complete measure of agricultural weather exposure.

The result is also consistent with the broader literature indicating that weather effects on labour markets may operate through wages, labour reallocation, non-farm employment and public employment rather than solely through aggregate employment.

## 8. ROBUSTNESS AND EXTENSIONS

The cross-sectional specification should be viewed as a baseline rather than the final identification strategy.

Several extensions are appropriate.

### 8.1 Southwest Monsoon Rainfall

The preferred future specification should replace annual rainfall departure with southwest monsoon rainfall departure because the monsoon is particularly important for agricultural production.

### 8.2 Rainfall Deficit and Surplus

The rainfall variable should be separated into:

$$RainDeficit_i = \max(0, -RainShock_i)$$

and

$$RainSurplus_i = \max(0, RainShock_i).$$

This would allow rainfall deficits and excess rainfall to have different coefficients.

### 8.3 Agricultural Dependence

The relationship should be interacted with the state's agricultural dependence:

$$RainShock_i \times AgricultureDependence_i.$$

This would test whether rainfall matters more in states where rural economic activity is more closely connected to agriculture.



## 8.4 Gender

Female rural WPR should be estimated separately. Household labour allocation may respond differently to rainfall and agricultural income shocks for women and men.

## 8.5 Panel Extension

The strongest future extension is a state-year panel covering 2017–18 to 2023–24:

$$RuralWPR_{it} = \alpha + \beta RainShock_{it} + \mu_i + \lambda_t + \epsilon_{it}.$$

Such a design would control for time-invariant state characteristics and common year shocks.

However, the panel specification should only be reported once the complete state-year dataset has been independently constructed and the regression has actually been estimated.

## 9. POLICY IMPLICATIONS

The findings have several policy implications, although they should be interpreted cautiously given the cross-sectional design.

First, rural employment policy should not rely exclusively on rainfall conditions as an indicator of labour-market stress. Employment outcomes depend on broader structural conditions.

Second, irrigation and water-management infrastructure can reduce rural economies' dependence on rainfall variability.

Third, diversification of rural employment can reduce household vulnerability to agricultural shocks.

Fourth, public employment programmes such as MGNREGA can potentially provide an adjustment mechanism when agricultural labour demand weakens. The empirical role of MGNREGA should be tested directly in future panel research.

Fifth, climate monitoring and labour-market monitoring should increasingly be integrated. State- and district-level employment indicators can be combined with high-resolution rainfall data to identify localised labour-market risks.

## 10. CONCLUSION

This study examined the association between rainfall departures from normal and rural employment across 28 Indian states using official secondary data for 2023.

The analysis combined IMD rainfall statistics with PLFS 2023–24 rural WPR for persons aged 15 years and above under usual status. The estimated rainfall coefficient was positive at 0.0803, with a robust standard error of 0.0792 and a p-value of 0.311. The model's  $R^2$  was 0.0275.

The empirical evidence therefore does not indicate a statistically significant linear relationship between the selected rainfall-shock measure and rural WPR across the 28 states in the sample.

This result should not be interpreted as evidence that rainfall is irrelevant to rural employment. Instead, it suggests that the aggregate state-level cross-sectional relationship is weak and that employment responses may operate through more complex mechanisms. Irrigation, agricultural structure, non-farm employment, migration, public employment and the timing of rainfall may all influence the observed relationship.

The main limitation of the study is its cross-sectional design. State-level observations cannot fully control for differences in economic structure and institutional conditions. Furthermore, a single year's rainfall measure cannot capture persistent climate exposure or dynamic employment responses.

Future research should therefore construct a multi-year state or district panel using PLFS and high-resolution rainfall data. Such a design would permit the inclusion of state and year fixed effects and provide a substantially stronger basis for examining within-state changes in rural employment following rainfall shocks.



## 11. LIMITATIONS

The study has five principal limitations.

**First**, the analysis is cross-sectional and therefore cannot establish causality.

**Second**, the sample contains only 28 state observations, limiting statistical power.

**Third**, rainfall departure is an aggregate measure and may not represent the rainfall experienced by individual agricultural households.

**Fourth**, annual rainfall departures do not capture the timing, intensity or spatial distribution of rainfall.

**Fifth**, important mediating factors including irrigation, agricultural dependence, migration, non-farm employment and MGNREGA are not included in the baseline regression.

These limitations should be explicitly recognised when interpreting the findings.

## 12. RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should:

1. Construct a 2017–18 to 2023–24 state-level panel.
2. Use southwest monsoon rainfall departures as the principal weather measure.
3. Include state and year fixed effects.
4. Separate rainfall deficits from rainfall surpluses.
5. Examine female rural WPR separately.
6. Include irrigation and agricultural dependence as moderators.
7. Examine MGNREGA employment as a potential adjustment mechanism.
8. Move from state-level to district-level rainfall exposure where data permit.
9. Use PLFS microdata to investigate individual-level labour responses.
10. Examine migration and non-farm employment as mechanisms.

## 13. DATA AVAILABILITY STATEMENT

The study uses publicly available secondary data from official Indian government sources.

The labour-market data are obtained from the Periodic Labour Force Survey published by the Ministry of Statistics and Programme Implementation.

The rainfall data are obtained from the India Meteorological Department's *Rainfall Statistics of India*.

The analytical sample and variables are derived from published state-level statistics.

## 14. DECLARATIONS

**Funding:** No external funding was received for this study.

**Conflict of Interest:** The author declares no conflict of interest.

**Ethical Approval:** The study uses publicly available secondary data and does not involve human participants or primary data collection.



**Author Contributions:** The author conceptualised the study, developed the methodology, analysed the secondary data and prepared the manuscript.

**Data Availability:** Data are derived from publicly available official government statistical publications.

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