Effect of Agricultural Shocks on the Business Cycle in India: A Theoretical Analysis

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Abstract

This study investigates the impact of agricultural shocks, particularly rainfall variability, on India's business cycle using a Real Business Cycle (RBC) framework. Extending Da-Rocha and Restuccia (2002), we incorporate land and rainfall shocks into a two-sector model. Using 1995–2024 data from five Indian states, we analyze correlations between rainfall, food grain production, irrigation, and agricultural GVA. Results highlight irrigation's role in mitigating shocks and agriculture's influence on output volatility.

1 Overview

This project examines how agricultural shocks, specifically rainfall variability, affect India's business cycle dynamics within a Real Business Cycle (RBC) framework. Building on Kydland and Prescott (1982, 1986) and Da-Rocha and Restuccia (2002), we extend a two-sector RBC model (agriculture and non-agriculture) by including land in the agricultural production function and modeling rainfall as a stochastic shock. The model is calibrated to India's agrarian economy, using data from 1995–2024 across five states to study labor reallocation, output volatility, and cyclical co-movements.

2 Motivation

Agriculture employs a significant portion of India's workforce but contributes modestly to GDP. Its reliance on monsoon-based irrigation makes it susceptible to rainfall shocks, impacting income, employment, and consumption. This project adapts the RBC framework to analyze these effects, focusing on agriculture's role in India's economic fluctuations.

3 Data and Correlation Analysis

3.1 Dataset

The analysis uses data from five Indian states (Uttar Pradesh, Punjab, West Bengal, Andhra Pradesh, Madhya Pradesh) from 1995–2024, comprising 150 observations (30 years $\times$ 5 states). Variables include:

- Rainfall (mm/year)

- Food Grain Production (million tonnes)
- Average Temperature ($^\circ$C)
- Irrigation Coverage (%)
- Rainfall Departure (%)
- Share of Agriculture GVA in GSVA (60 observations, Uttar Pradesh and Madhya Pradesh)

3.2 Correlation Results

Pearson correlations with rainfall:

- Food Grain Production: $r = 0.15$ (weak positive)
- Average Temperature: $r = -0.10$ (very weak negative)
- Irrigation Coverage: $r = -0.25$ (weak negative)
- Rainfall Departure: $r = 1.00$ (perfect positive)
- Share of Agriculture GVA: $r = 0.20$ (weak positive)

The weak rainfall-food grain correlation ($r = 0.126$) underscores irrigation's mitigating role, with a strong irrigation-output correlation ($r = 0.862$).

4 Literature Review

- **Chuang (2018)**: A 10% rainfall drop reduces household income by 8% and agricultural income by 15%. Farmers adapt via non-farm work.
- **Brey & Hertweck (2023)**: Regional droughts cut crop yields by 30%, wages by 7%, and raise food prices by 5%. Irrigation mitigates impacts.
- **Panda et al. (2019)**: Rainfall drives 73% of rice and 54% of maize yield variations in Odisha.
- **Bora (2022)**: Previous-year rainfall shocks reduce fertilizer use by 4%, but intense droughts increase it.
- **Da-Rocha & Restuccia (2002)**: Agriculture's counter-cyclical employment and high volatility influence business cycles.
- **Pandey, Patnaik & Shah (2018)**: Pre-1991 cycles were monsoon-driven; post-1991 cycles reflect investment fluctuations.

4.1 Research Gaps

- Limited analysis of climate shocks' impact on agricultural productivity and labor dynamics.
- Need for state- or crop-specific studies.
- Lack of demand-side and infrastructure modeling in RBC frameworks.

5 Methodology

1. **Model Extension**: Added land to the agricultural production function and modeled rainfall shocks.
2. **Shock Introduction**: Rainfall variability as a stochastic shock in sector-specific TFP.
3. **Calibration**: Parameters reflect India's agrarian economy, using empirical rainfall data.
4. **Simulation**: Analyzes labor reallocation, output volatility, and cyclical co-movements.

6 Model Formulation

6.1 Utility Function

$$U(C_t, l_t) = b \log[\alpha C_{n,t} + (1-\alpha) C_{a,t}] + (1-b) \log[(1-h_a)^{\pi_{a,t}} (1-h_n)^{\pi_{n,t}}]$$

where C_t is total consumption, l_t is leisure, h_a, h_n are labor hours, and $\pi_{a,t}, \pi_{n,t}$ are labor shares.

6.2 Capital Allocation

$$K_t = K_{a,t} + K_{n,t}, \quad K_t = X_t + (1-\delta) K_{t-1}$$

6.3 Aggregate Output

$$Y_t = \alpha Y_{n,t} + (1-\alpha) Y_{a,t} = \alpha C_{n,t} + (1-\alpha) C_{a,t} + X_t$$

6.4 Production Functions

$$Y_{n,t} = A_{n,t} K_{n,t-1}^{\theta} H_{n,t}^{1-\theta}, \quad Y_{a,t} = A_{a,t} K_{a,t-1}^{\mu} H_{a,t}^{\phi} T^{1-\mu-\phi}$$

6.5 TFP Processes

$$\log A_{a,t} = (1-\rho) \log A_a^S + \rho \log A_{a,t-1} + \varepsilon_t, \quad \log A_{n,t} = (1-\rho) \log A_n^S + \rho \log A_{n,t-1} + \varepsilon_t$$

6.6 Social Planner's Problem

Maximize:

$$\max_{\{C_{t+i}, \ell_{t+i}\}} \mathbb{E}_t \left[\sum_{i=0}^{\infty} \beta^i \left(b \log C_{t+i} + (1-b) \log \ell_{t+i} \right) \right]$$

Subject to resource constraints, solved via Lagrangian and log-linearization.

7 Results

7.1 Benchmark (U.S.-like, $s_a = 0.02$)

- Output volatility (σ_Y): 2.00 (vs. 2.12 actual)
- Employment volatility (σ_L/σ_Y): 0.65 (vs. 0.63)
- Employment-output correlation ($\rho(L, Y)$): 0.80 (vs. 0.82)
- Agri. employment vs. non-agri. output ($\rho(L_a, Y_n)$): -0.10 (vs. -0.14)

7.2 High Agricultural Share (Turkey-like, $s_a = 0.20$)

- σ_Y: 2.74 (36% increase)
- σ_L/σ_Y: 0.49
- $\rho(L, Y)$: 0.52

7.3 Empirical Correlations (India, 1995–2024)

- Irrigation vs. Food Grain: $r = 0.862$
- Avg. Temperature vs. Food Grain: $r = 0.705$
- Rainfall vs. Food Grain: $r = 0.126$
- Agri. GVA vs. Food Grain (UP & MP): $r = -0.784$

7.4 Conclusion

Agriculture dampens employment volatility through reallocation and drives output fluctuations in agri-intensive economies.

8 Discussions

The results validate agriculture's counter-cyclical role (Da-Rocha & Restuccia, 2002). Strong irrigation-output correlation ($r = 0.862$) highlights infrastructure's importance, while weak rainfall correlation ($r = 0.126$) suggests resilience. The negative GVA correlation ($r = -0.784$) supports convergence. Limitations include annual data granularity and lack of demand-side modeling.

9 Conclusion

This study reaffirms agriculture's pivotal role in India's business cycle. Irrigation and diversification enhance resilience. As agricultural shares decline, global business cycle convergence is likely. Policymakers should prioritize infrastructure investments.

10 References

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11 Data Sources

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