Effect of agricultural shocks on the business cycle in India- A theoretical analysis

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ABSTRACT

- ❑ The seminal papers of of Kydland and Prescott (1982) and Prescott (1986), RBC theory provided the main reference framework for the analysis of economic fluctuations and became to a large extent the core of macro-economic theory.
- ❑ However, in India the use of dynamic stochastic general equilibrium models(DSGE) within the RBC framework has not become prevalent. In fact the interest in analysis of business cycles in India is relatively recent.
- ❑ Our presentation looks to use the RBC framework in an Indian context, particularly by including the agriculture sector within the framework. We base our presentation primarily on the work of Da Rocha and Restuccia (2002), as well as drawing motivation from the large body existing literature

MOTIVATION

- ❖ The agriculture sector is a driving force of the Indian economy, it employs the most people throughout the year however its contribution to overall GDP is quite limited. Still it forms the backbone of the economy.
- ❖ We incorporate the agricultural sector in a two sector RBC model, and try to look for the responses of the real variables namely Income, Employment and Consumption to shocks affecting agriculture. Mainly we look at variability in patterns of rainfall over time as the agricultural sector in India is still primarily still heavily reliant on monsoon based irrigation

Research Motivation On Rainfall and Agricultural Variables

Introduction to Data and Correlation Analysis

Dataset Overview:

- ➢ Agricultural data from 5 Indian states (Uttar Pradesh, Punjab, West Bengal,Andhra Pradesh, Madhya Pradesh), 1995–2024.
- ➢ Variables: Rainfall (mm/year), Food Grain Production (million tonnes), Avg. Temperature (◦C), Irrigation Coverage (%), Rainfall Departure (%), Share of Agriculture GVA in GSVA (%).
- ➢ 150 observations (30 years × 5 states); GVA share limited to 60 observations (Uttar Pradesh & Madhya Pradesh).

Correlation Results (Pearson Correlation with Rainfall):

- **Food Grain Production:** r = 0.15 (Weak positive; slight increase with rainfall).
- **Avg. Temperature:** r = −0.10 (Very weak negative; minimal linear relation).
- **Irrigation Coverage:** r = −0.25 (Weak negative; lower rainfall linked to higher irrigation).
- **Rainfall Departure:** r = 1.00 (Perfect positive; expected due to direct relation).
- **Share of Agriculture GVA:** r = 0.20 (Weak positive; limited data, slight economic impact).

Need for Future Study

Why Rainfall Isn’t Enough:
The data shows weak links between rainfall and agricultural outcomes, suggesting that other factors like irrigation, crop variety, and technology also play a significant role.
Data Limitations:
Economic data is limited to two states, which may not represent the national picture.
Combining data from five states could obscure regional trends.
Why Climate Context Matters:
Climate change is making rainfall patterns more unpredictable, highlighting the need to understand its impact on crops and regions, especially in the face of potential droughts and floods.
What Needs to Be Done:
Future studies should focus on state- or crop-specific analysis and use regression models to account for multiple factors, helping policymakers develop more targeted agricultural policies.

Literature Review

- **Climate Variability, Rainfall Shocks, and Farmers' Income Diversification in India (Yating Chuang, 2018):** A 10% drop in rainfall relative to its 20-year average is linked to an 8% decline in total household income and a 15% decrease in agricultural income. Farmers adapt by boosting non-farm wage work—including agricultural wage jobs—while regions with low historical rainfall variability prove especially vulnerable due to minimal pre-adaptation.

- **The Dynamic Effects of Monsoon Rainfall Shocks on Agricultural Yield, Wages, and Food Prices in India (Brey & Hertweck, 2023):** This study shows that when India experiences a regional drought, crop yields can drop by as much as 30%, compared to a 15% decline during local droughts; extra rainfall, on the other hand, only slightly boosts yields. Even though crop production recovers quickly, wages fall by up to 7%—with the worst drop occurring about two years after the drought and lasting up to five years—while food prices remain around 5% higher for up to two years. Better irrigation helps lessen these negative effects.

Literature Review

- **Impact of Climate Variability on Crop Yield in Kalahandi, Bolangir, and Koraput Districts of Odisha, India (Panda et al., 2019):** This study analyzes 38 years of climate data and 37 years of crop yield records for rice and maize. It shows that rainfall changes are the main driver of yield differences—explaining about 73% of rice yield and 54% of maize yield variations—while temperature changes have a smaller effect. The Indian Summer Monsoon is crucial for sustaining crop productivity in these vulnerable districts.

- **Rainfall shocks and fertilizer use: a district level study of India (Bora, 2022):** Using panel data from 311 districts (1966–2009), the study finds that while fertilizer use remains largely unchanged during a negative rainfall shock in the current year, a negative rainfall shock in the previous year cuts fertilizer application by about 4% per hectare. Moreover, when droughts are more intense in the preceding year, farmers tend to boost fertilizer use—suggesting an adaptive response. Higher irrigation levels are also tied to greater fertilizer consumption.

Literature Review

- **The Role of Agriculture in Aggregate Business Cycle Fluctuations (Da-Rocha & Restuccia, 2002)**

  Key Findings: Agriculture, despite its small share in developed economies (e.g., 1.75% of U.S. GDP), significantly influences business cycle dynamics. Agricultural employment is counter-cyclical, and its high volatility helps resolve issues in standard RBC models, such as excessive employment fluctuations and unrealistic labor-productivity correlations. Cross-country analysis shows that agricultural intensity correlates with higher output fluctuations and lower employment volatility—for example, Turkey (30% agricultural employment) has greater output volatility ($\sigma Y = 3.25$) and lower employment-output correlation ($\rho(L, Y) = 0.13$) compared to the U.S. ($\sigma Y = 2.12$, $\rho(L, Y) = 0.82$).
  Research Gap: While the study highlights agriculture's role in business cycles, it does not explore how climate shocks, such as rainfall variability, directly impact agricultural productivity and sectoral labor dynamics.

Literature Review

- **Business Cycle Measurement in India (Pandey, Patnaik & Shah, 2018)**

  Key Findings: This study presents the business cycle chronology for India, identifying two distinct phases. The pre-1991 period saw cycles primarily driven by monsoon shocks, with downturns linked to droughts or oil price hikes. The post-1991 phase marked the emergence of conventional business cycles, driven by investment-inventory fluctuations. The study also examines economic conditions shaping these cycles, including structural reforms following the 1990-91 Balance of Payments crisis.
  Research Gap: While the paper provides a historical perspective on Indian business cycles, further research is needed on how agriculture-specific shocks, such as rainfall variability, influence sectoral employment and output within the RBC framework.

INTRODUCTION

❖ Da Rocca and Restuccia (2002) analyzed how agriculture responds to macroeconomic variables, policy, and random shocks using a reduced-form VAR model.

❖ We modify the model in two key ways:

- **Land use** is explicitly included in the production function.
- **Rainfall variability** is modeled as an endogenous shock affecting output.

❖ This reflects real-world climate-agriculture interactions and strengthens the model's predictive and policy relevance.

METHODOLOGY

1. Model Extension
    - Built on Da Rocha & Restuccia's (2002) two-sector RBC framework (agriculture & non-agriculture).
    - Introduced **land** as an explicit input in the agricultural production function.
2. Shock Introduction
    - Modeled **rainfall variability** as a stochastic shock affecting agricultural productivity.
    - Rainfall shocks incorporated into a sector-specific TFP process.
3. Calibration
    - Calibrated to reflect typical characteristics of an agrarian economy.
    - Used empirical rainfall data patterns to parameterize shock processes.
4. Simulation & Analysis
    - Ran dynamic simulations to observe sectoral and aggregate responses to shocks.
    - Analyzed labor reallocation, output volatility, and cyclical co-movements.
    - Compared model outputs with baseline (no rainfall shock) to assess impact.

Forming the Model:

Consumers choose between consumption and leisure in each period. The utility function is given by:

$$U = U(C_t, l_t) \tag{1}$$

where

$$C_t = \alpha C_{n,t} + (1-\alpha)C_{a,t} \tag{2}$$

and

$$l_t = (1-h_a)^{\pi_{a,t}}(1-h_n)^{\pi_{n,t}} \tag{3}$$

Thus, the utility function becomes:

$$U(C_t, l_t) = b\log\left[\alpha C_{n,t} + (1-\alpha)C_{a,t}\right] + (1-b)\log\left[(1-h_a)^{\pi_{a,t}}(1-h_n)^{\pi_{n,t}}\right] \tag{4}$$

Fixed capital K_t is distributed evenly across the two sectors:

$$K_t = K_{a,t} + K_{n,t}, \quad \text{for each } t \tag{5}$$

Overall capital accumulation is given by:

$$K_t = X_t + (1-\delta)K_{t-1} \tag{6}$$

where X_t represents investment.

Social Planner’s Optimization Problem

The aggregate output of the economy is given by:

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

The social planner chooses sequences $\{C_{t+i}, \ell_{t+i}\}_{i=0}^{\infty}$ to maximize expected lifetime utility:

$$\max_{\{C_{t+i}, \ell_{t+i}\}} \mathbb{E}_t \left[\sum_{i=0}^{\infty} \beta^i \left(b \log(C_{t+i}) + (1-b) \log(\ell_{t+i}) \right) \right] \tag{2}$$

Subject to the following constraints:

$$C_{n,t} + (K_t - (1-\delta) K_{t-1}) = Y_{n,t} = A_{n,t} K_{n,t-1}^{\theta} H_{n,t}^{1-\theta} \tag{3}$$

$$C_{a,t} = Y_{a,t} = A_{a,t} K_{a,t-1}^{\mu} H_{a,t}^{\phi} T^{1-\mu-\phi} \tag{4}$$

$$K_t = X_t + (1-\delta) K_{t-1} \tag{5}$$

$$\log A_{a,t} = (1-\rho) \log(A_a^S) + \rho \log A_{a,t-1} + \varepsilon_t \tag{6}$$

$$\log A_{n,t} = (1-\rho) \log(A_n^S) + \rho \log A_{n,t-1} + \varepsilon_t \tag{7}$$

where:

- Y_t: Aggregate output $Y_{n,t}, Y_{a,t}$: Non-agricultural and agricultural output
- $C_{n,t}, C_{a,t}$: Sectoral consumption C_t: Total consumption
- X_t: Investment/output residual K_t: Total capital
- $K_{n,t-1}, K_{a,t-1}$: Sectoral capital from previous period
- $H_{n,t}, H_{a,t}$: Labor in each sector ℓ_t: Leisure
- T: Land (assumed fixed)
- $A_{n,t}, A_{a,t}$: Sector-specific productivity
- β: Discount factor b: Preference for consumption
- θ, μ, ϕ: Output elasticities
- δ: Capital depreciation rate
- ρ: TFP autocorrelation ε_t: i.i.d. shock
- A_n^S, A_a^S: Steady-state productivity levels

The Lagrangian is formed as shown below:

$$
\begin{aligned}
L = {} & E_t \sum_{i=0}^{\infty} \beta^i \left[b \log C_{t+i} + (1-b) \log \ell_{t+i} \right] \\
& + E_t \sum_{i=0}^{\infty} \beta^i \lambda_{1,t+i} \left[\alpha \left(A_{n,t+i} K^{\theta}_{n,t-1+i} (\pi_{n,t+i}, \bar{h}_n)^{1-\theta} - C_{n,t+i} \right) - K_{n,t+1} + (1-\delta) K_{n,t-1+i} \right] \\
& + E_t \sum_{i=0}^{\infty} \beta^i \lambda_{2,t+i} \left[(1-\alpha) \left(A_{a,t+i} K^{\mu}_{a,t+i} (\pi_{a,t+i}, \bar{h}_a)^{\phi} T^{1-\mu-\phi} - C_{a,t+i} \right) - K_{a,t+i} + (1-\delta) K_{t-1+i} \right]
\end{aligned}
$$

The period t optimization problem is as follows:

$$
\begin{aligned}
L = {} & b \log\left[\alpha C_{n,t} + (1-\alpha) C_{a,t}\right] + (1-b)\left[\pi_{n,t}\log(1-\bar{h}_n) + \pi_{a,t}\log(1-\bar{h}_a)\right] \\
& + \lambda_{1,t}\left[\alpha\left(A_{n,t}K^{\theta}_{n,t-1}(\pi_{n,t}, \bar{h}_n)^{1-\theta} - C_{n,t}\right) - K_{n,t} + (1-\delta)K_{n,t-1}\right] \\
& + \lambda_{2,t}\left[(1-\alpha)\left(A_{a,t}K^{\mu}_{a,t-1}(\pi_{a,t}\bar{h}_a)^{\phi}T^{1-\mu-\phi} - C_{a,t}\right) - K_{a,t} + (1-\delta)K_{n,t-1}\right] \\
& + \beta E_t\Big[\lambda_{1,t+1}\left(\alpha\left(A_{n,t+1}K^{\phi}_{n,t}(\pi_{n,t+1}, \bar{h}_n)^{1-\theta}\right) + (1-\delta)K_{n,t}\right) \\
& \quad + \lambda_{2,t+1}\left((1-\alpha)\left(A_{a,t+1}K^{\mu}_{a,t}(\pi_{a,t+1}\bar{h}_a)^{\phi}T^{1-\mu-\phi}\right) + (1-\delta)K_{a,t}\right)\Big]
\end{aligned}
$$

Equations Formed After Log Linearization:

$$\hat{y}_t = \left(\frac{\bar{c}}{\bar{y}}\right)\hat{c}_t + \left(\frac{\bar{x}}{\bar{y}}\right)\hat{x}_t$$

$$\hat{c}_t = \frac{\beta}{L} \cdot E_t\left[2\hat{c}_{t+1} + \hat{r}^k_{a,t+1} + \hat{r}^k_{n,t+1}\right]$$

$$\hat{k}_t = \hat{k}_{a,t} + \hat{k}_{n,t}$$

$$\hat{k}_t = \left(\frac{\bar{x}}{\bar{k}}\right)\hat{x}_t + (1-\delta)\hat{k}_{t-1}$$

$$\hat{y}_t = \alpha(\hat{y}_{n,t} - \hat{y}_{a,t}) + \hat{y}_{a,t}$$

$$\hat{r}^k_{a,t} = \alpha\theta(\hat{y}_{a,t+1} - \hat{k}_{a,t}) + (1-\delta) \quad \text{(return on `a')}$$

$$\hat{r}^k_{n,t} = (1-\alpha)\mu(\hat{y}_{n,t+1} - \hat{k}_{n,t}) + (1-\delta) \quad \text{(return on `n')}$$

$$\hat{a}_{a,t} = (1-e)\hat{a}_a + \rho\hat{a}_{a,t-1} + \varepsilon_t$$

$$\hat{a}_{n,t} = (1-e)\hat{a}_n + \rho\hat{a}_{n,t-1} + \varepsilon_t$$

Steady State Equations:

$$\bar{y} = \bar{c} + \bar{x}$$

$$\bar{R}_{a,t} + \bar{R}_n = \frac{L}{\beta}$$

$$\mathcal{S} = \frac{\bar{X}}{\bar{K}}$$

$$\bar{R}_a = \alpha\theta \cdot \frac{Y_a}{K_a} + (1-\delta)$$

$$\bar{R}_n = (1-\alpha) \cdot \mu \cdot \frac{Y_m}{K_m} + (1-\delta)$$

$$(1-b) \cdot \log(1-\bar{h}_a) + (B \cdot \bar{c}^{-1}) \cdot \left[(1-\theta) \cdot \alpha \cdot \frac{Y_a}{\Pi_{n,t}}\right] = 0$$

$$(1-b) \cdot \log(1-\bar{h}_a) + (B \cdot \bar{c}^{-1}) \cdot \left[\Phi \cdot (1-\alpha) \cdot \frac{Y_m}{\Pi_{n,t}}\right] = 0$$

RESULTS

- **Benchmark (U.S.-like, sa = 0.02):**
  - Output volatility (σY): 2.00 (vs. 2.12 actual)
  - Employment volatility ($\sigma L/\sigma Y$): 0.65 (vs. 0.63)
  - Employment-output correlation ($\rho(L, Y)$): 0.80 (vs. 0.82)
  - Agri. employment vs. non-agri. output ($\rho(La, Yn)$): –0.10 (vs. –0.14)
- **High Agri Share (Turkey-like, sa = 0.20):**
  - σY rises to 2.74 → 36% increase
  - $\sigma L/\sigma Y$ drops to 0.49 → Lower employment volatility
  - $\rho(L, Y)$ falls to 0.52 → Weaker labor-output link

- **Empirical Correlations (India, 1995–2024):**
  - Irrigation vs. Food Grain: **r = 0.862**
  - Avg. Temp vs. Food Grain: **r = 0.705**
  - Rainfall vs. Food Grain: **r = 0.126**
  - Agri. GVA share vs. Food Grain (UP & MP): **r = –0.784**
- **Conclusion:**
  - Agriculture **dampens employment volatility** via reallocation.
  - In agri-intensive economies, **agriculture drives output fluctuations**

DISCUSSIONS

The results validate Da-Rocha & Restuccia (2002)'s view that agriculture's counter-cyclical nature and high volatility significantly influence business cycles, with labor reallocation dampening employment fluctuations—especially in agri-intensive economies. Strong irrigation–output correlation ($r = 0.862$) in India underscores the role of infrastructure, while the weak rainfall correlation ($r = 0.126$) suggests irrigation mitigates weather shocks. The negative agri-GVA correlation ($r = –0.784$) supports the convergence hypothesis. Limitations include annual data masking short-run dynamics and lack of demand-side or infrastructure modeling. Future work should integrate these elements to enhance relevance for policy in agri-driven economies.

CONCLUSION

This study reaffirms agriculture's pivotal role in business cycle dynamics, as shown by Da-Rocha & Restuccia (2002). Their two-sector RBC model explains counter-cyclical employment and cross-country differences. Indian data highlights the importance of irrigation and diversification. As agricultural shares decline, global business cycles may converge (Backus & Kehoe, 1992). Policymakers should invest in agricultural infrastructure, and future models should integrate both supply and demand shocks.

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For Data:

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- Food And agricultural Dept(FAV).
- Food and Agricultural Organisation (FAO).

THANK YOU