# Climate Shocks and Inflation in Indian States: A Local Projections Approach

*Climate Policy, Environment and Macroeconomics*

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# 1 Introduction

Climate shocks such as rainfall shocks and extreme temperature are no longer only an environmental concern; they are increasingly a macroeconomic and policy challenge. In an economy such as India, where food prices remain highly sensitive to weather conditions and where regional production structures differ sharply across states, abnormal rainfall and temperature shocks can quickly translate into inflationary pressures. Inflationary pressures affect household welfare, but also have sharp policy implications affecting fiscal and monetary policy. However, the transmission of these climate shocks into prices is unlikely to be uniform across regions. Some shocks may generate immediate supply disruptions, while others may operate with lags through harvest losses, transport bottlenecks, storage constraints, and adjustment in local markets.

This paper studies how weather shocks affect state-level inflation dynamics in India. We focus on precipitation and temperature anomalies at the state-level and estimate their effects on state-level headline inflation (general) as well as on two key sub-components: food and beverages, and fuel and light. This disaggregation is important because climate shocks do not affect all prices through the same channel. Food inflation is expected to respond directly through agricultural production and perishability, whereas fuel and other non-food components may react more indirectly through transportation costs, and energy demand. Looking only at aggregate inflation will not allow us to understand which component of inflation is driving the aggregate trend in inflation due to the shocks.

The paper uses the Local Projections framework to trace the dynamic response of inflation to rainfall shocks over a twelve-month horizon. This approach is well suited to the present setting because it allows impulse responses to be estimated flexibly without imposing the strong dynamic restrictions in the vector autoregressive model. Our empirical design is built around state-level monthly data and a specification that progressively introduces stricter controls, including state-year and year-month fixed effects. This strategy helps isolate plausibly exogenous variation in local weather from broader macroeconomic shocks and from persistent state-specific factors.

The contribution of the paper is twofold. First, it adds to the growing literature on climate and macroeconomic outcomes by providing sub-national evidence for India using local projections. Although, the impact of climate shocks on national-level inflation has been studied using local projections, no study has been conducted using state-level inflation as per our knowledge. Second, it connects climate risk to inflation heterogeneity, showing why the inflationary consequences of weather shocks may depend both on the composition of the consumption basket and on state-level economic resilience. In a policy environment where both inflation control and climate adaptation are becoming more urgent, understanding these transmission channels and the persistence of climate shocks on inflation is essential.

# 2 Motivation and Research Question

The primary motivation for this paper is the economic relevance of the outcome variable. Inflation directly affects household purchasing power, real wages, poverty, and welfare. In India, this is especially true because food occupies a large share of household consumption, particularly for poorer households. As a result, even temporary weather shock induced price increases can have consequences for living standards. Inflation also have an effect on policy as climate shocks generate persistent inflationary pressures, that can affect monetary policy, fiscal responses, and influence the design of food management and market stabilization measures. For these reasons, state-level inflation is an economically important outcome to study.

A second motivation is that rainfall shocks have clear theoretical channels through which they may affect inflation. The most immediate channel is food prices. Droughts can reduce the yields of staple crops such as cereals and pulses, creating supply shortages that put upward pressure on retail prices. Floods can destroy perishable crops such as tomatoes and onions and can also disrupt rural roads, storage, and local transport networks, generating sudden spikes in market prices even when the production shock itself is localized. These mechanisms imply that rainfall shocks can affect both the availability of food and the efficiency with which food reaches the markets and the consumers.

Rainfall shocks may also influence fuel and energy prices. Drought conditions can reduce hydropower availability and increase dependence on diesel-powered irrigation and other costly energy inputs. Floods can damage infrastructure and disrupt coal extraction and transport, raising the cost of thermal power generation. Temperature shocks can result in increased demand for energy leading to a rise in energy prices.

These channels are unlikely to operate uniformly across Indian states. States differ in crop composition, irrigation intensity, storage capacity, market connectivity, and dependence on climate-sensitive sectors. As a result, the same rainfall shock may generate very different inflationary responses across regions. Examining state-level inflation alongside state-level climate shocks therefore allows us to identify how these shocks transmit at the subnational level and to better understand their average effects across India.

Taken together, this paper addresses the following research questions. The primary question is: how do localized precipitation and temperature shocks affect the magnitude and persistence of state-level inflation in India? The first sub-question is: how many months does it take for a rainfall shock to fully pass through to retail food prices, energy prices, and general inflation levels? The second sub-question is whether state-level economic capacity plays a role in shaping these inflationary responses, which we examine through the rich-poor state analysis.

# 3 Literature Review

## 3.1 Global Evidence on Climate Shocks and Macroeconomic Outcomes

Climate change is increasingly recognized as a critical macroeconomic risk that significantly impacts inflation and output dynamics globally (Cevik and Jalles, 2023; Qi et al., 2025). Evaluating a large panel of countries, Cevik and Jalles (2023) highlight that climate-induced natural disasters have highly heterogeneous effects across different income groups. Specifically, they find that extreme temperatures tend to reduce inflation in developing countries, whereas droughts and storms lead to higher inflation levels. Conversely, Qi et al. (2025) assess global economies using the Generalized Method of Moments (GMM) and note that climate change acts primarily as a short-term supply shock that exacerbates inflation, particularly in low-income nations. This inflationary pressure is transmitted heavily through central bank interest rate policies and food price channels, though the effects dissipate in the long term (Qi et al., 2025).

## 3.2 Evidence from India: Inflation and Output Dynamics

Within the Indian context, the empirical consensus strongly links climate shocks to inflationary pressures. Using state-level panel data, Sahu et al. (2026) demonstrate that temperature anomalies and rainfall deficits exert upward pressure on state-level inflation. Similarly, Kumar (2025) employs SVAR and TV-VAR models to show that rising temperatures Granger-cause inflation in India, specifically driving up food, housing, and energy prices. However, multiple studies indicate that while climate shocks significantly alter prices, their aggregate impact on output growth in India often remains statistically insignificant (Kumar, 2025).

Food prices consistently emerge as the most sensitive component to climate variability. Sahu et al. (2026) reveal that food inflation reacts much more sharply to climate anomalies than general CPI inflation, emphasizing that agricultural supply disruptions are the primary transmission mechanism. Kumar et al. (2026) utilize local projections to trace the dynamic effects of specific shocks on Indian food inflation, finding severe heterogeneity depending on the disaster type. They observe that drought intensity raises cumulative food inflation in the medium run, peaking around the fourth year, while floods cause short-run disinflation, followed by a delayed inflationary catch-up as stabilization policies unwind (Kumar et al., 2026).

# 4 Data

The empirical analysis combines state-level inflation data with high-resolution climate data to construct a monthly panel for Indian states and union territories. The final dataset links inflation outcomes to localized precipitation and temperature shocks at the state-month level.

## 4.1 Inflation Data

Inflation data are drawn from the Ministry of Statistics and Programme Implementation (MoSPI) Consumer Price Index series at the state level. The sample covers monthly observations from January 2014 to December 2025. We study three outcome variables: general inflation, food and beverages inflation, and fuel and light inflation. State-level inflation is computed as the year-on-year log difference in the relevant CPI index. The broad composition of headline CPI under the 2012=100 base. General inflation is divided into major sub-components including Food and Beverages (45.86%), Miscellaneous (28.32%), Housing (10.07%), Fuel and Light (6.84%), Clothing and Footwear (6.53%), and Pan, Tobacco, and Intoxicants (2.38%). State-specific weights differ according to regional consumption patterns.

## 4.2 Climate Data and Shock Construction

Climate data are obtained from the Copernicus ERA5 reanalysis product, which provides high-resolution daily temperature and precipitation measures on a $0.1^\circ \times 0.1^\circ$ grid. These gridded observations are aggregated to state boundaries using area-weighted zonal statistics to obtain state-level monthly climate measures. We then construct standardized climate anomalies using a 30-year historical window for each state-month.

Specifically, the precipitation shock is defined as:

$$PrecipShock_{s,m,t} = \frac{P_{s,m,t} - \bar{P}_{s,m}}{\sigma_{s,m}} \tag{1}$$

where $P_{s,m,t}$ denotes precipitation in state $s$, month $m$, and year $t$, while $\bar{P}_{s,m}$ and $\sigma_{s,m}$ are the 30-year mean and standard deviation for that state-month. This measure captures the deviation of observed precipitation from the climatological normal and is therefore interpreted as a $Z$-score.

Similarly, the temperature shock is defined as:

$$TempShock_{s,m,t} = \frac{T_{s,m,t} - \bar{T}_{s,m}}{\sigma_{s,m}} \tag{2}$$

where $T_{s,m,t}$ denotes temperature in state $s$, month $m$, and year $t$, and $\bar{T}_{s,m}$ and $\sigma_{s,m}$ are the corresponding 30-year state-month mean and standard deviation. This measure isolates extreme heat realizations relative to regular seasonal patterns and is likewise interpreted as a standardized anomaly. In the empirical analysis, these measures are recorded as `Precip_Shock` and `Temp_Shock`.

# 5 Summary Statistics

Table 1 presents the descriptive statistics. The climate shock variables remain standardized and centered close to zero, while the inflation measures are reported as year-over-year percentage changes. The shock variable means are not exactly zero as a rolling window is used to calculate the z-score. Headline inflation averages 5.05% across the sample, food and beverages inflation averages 4.96%, and Fuel and Light inflation remains the most volatile component with a standard deviation of 7.94%.

Table 1: Descriptive Statistics of Inflation and Climate Variables

| **Variable** | **N** | **Mean** | **St. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| Precip_Shock | 5,243 | 0.07 | 1.02 | -2.49 | 5.03 |
| Temp_Shock | 5,243 | 0.54 | 1.01 | -3.23 | 3.16 |
| Inf_General_Index_All_Groups | 4,825 | 5.05 | 2.63 | -4.23 | 20.70 |
| Inf_Food_and_beverages | 4,627 | 4.96 | 4.30 | -9.34 | 27.45 |
| Inf_Fuel_and_light | 4,627 | 5.17 | 7.94 | -29.62 | 57.82 |

*Notes:* Observations are at the state-month level. Shocks are localized $Z$-scores; inflation metrics are Year-over-Year percentage changes.

# 6 Methodology and Empirical Strategy

To trace the dynamic pass-through of climate shocks to state-level inflation, this study employs the Local Projections (LP) framework by Jordà (2005). The LP method does not impose dynamic restrictions, making it highly robust to misspecification, especially when dealing with persistent macroeconomic variables across mixed frequencies.

The core econometric challenge in sub-national climate analysis is isolating the purely exogenous climate shock from overlapping economic policies and yearly trends. However, there is no scope for endogeneity in our model as the climate shocks are assumed to be exogenous. To reduce ommitted variable bias and improve causal identification, our baseline model for horizon $h = 0, 1, \ldots, 12$ relies on two-way fixed effects:

$$\begin{aligned}\pi_{i,t+h} = \alpha_{i,y}^{(h)} + \gamma_t^{(h)} + \beta^{(h)}\text{Precip\_Shock}_{i,t} + \theta^{(h)}\text{Temp\_Shock}_{i,t} \\ + \sum_{j=1}^{2}\rho_j^{(h)}\pi_{i,t-j} + \sum_{j=1}^{2}\delta_j^{(h)}\mathbf{S}_{i,t-j} + \epsilon_{i,t+h}^{(h)}\end{aligned} \tag{3}$$

Where:

- $\pi_{i,t+h}$ represents the year-over-year inflation rate for state $i$ at time $t + h$ (General, Food and Beverages, or Fuel and Light).
- $\text{Precip\_Shock}_{i,t}$ is the standardized precipitation shock ($Z$-score) for state $i$ at time $t$. The coefficient of interest is $\beta^{(h)}$, which traces the impulse response function (IRF).
- $\text{Temp\_Shock}_{i,t}$ is the standardized temperature shock ($Z$-score) for state $i$ at time $t$.
- $\alpha_{i,y}^{(h)}$ represents the **State-Year Fixed Effect** (where $y$ denotes the year of observation $t$). This absorbs all state-level variations that occur at an annual frequency, including local agricultural policy shifts and state budget expenditures.
- $\gamma_t^{(h)}$ represents the **Time (Year-Month) Fixed Effect**, which controls for national macroeconomic shocks.
- $\mathbf{S}_{i,t-j}$ represents the lagged values of climate shocks, controlling for persistence of climate shocks.
- $\pi_{i,t-j}$ represents the autoregressive lags (2 months) of the dependent variable to control for inflation persistence.

Standard errors are clustered at the state level across all models to correct for arbitrary serial correlation across months and years within the same state. The specification presented above is the most stringent model and we also experiment with other forms of fixed effects.

# 7 Results

The dynamic pass-through of precipitation shocks to inflation is captured via the Local Projection IRFs across a 12-month horizon and the coefficients are reported at 90% confidence interval.

## 7.1 General Inflation

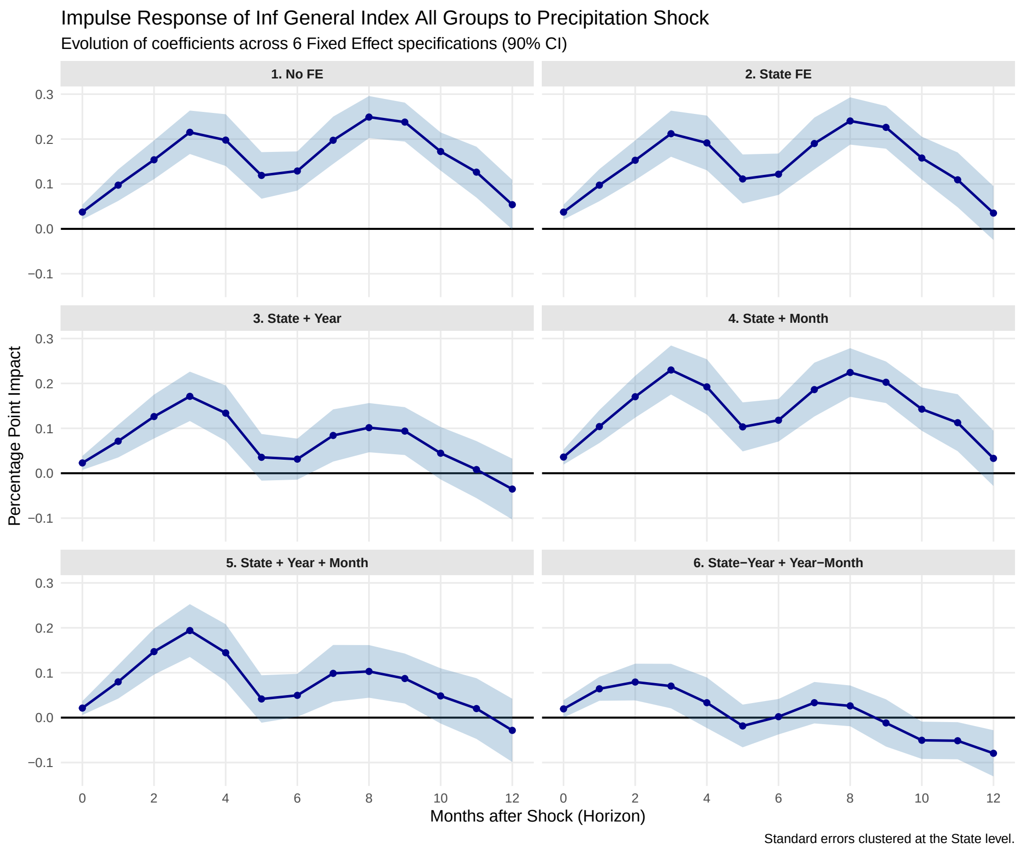


Figure 1: Local Projection Results for General Inflation

Figure 1 presents the impulse response of general inflation to a one standard deviation precipitation shock across six fixed effects specifications. In the baseline specifications with no fixed effects or only state fixed effects (panels 1-2), precipitation shocks exhibit a positive and statistically significant impact on general inflation, peaking around 3-4 months after the shock at approximately 0.20-0.25 percentage points. However, as we introduce more stringent controls, the estimated effects reduce substantially. In our most restrictive specification (panel 6), the response becomes smaller and loses statistical significance for the later months. This pattern suggests that much of the apparent inflationary impact observed in simpler models reflects omitted state-specific trends and national macroeconomic factors rather than the direct effect of localized precipitation shocks.

## 7.2 Food Inflation

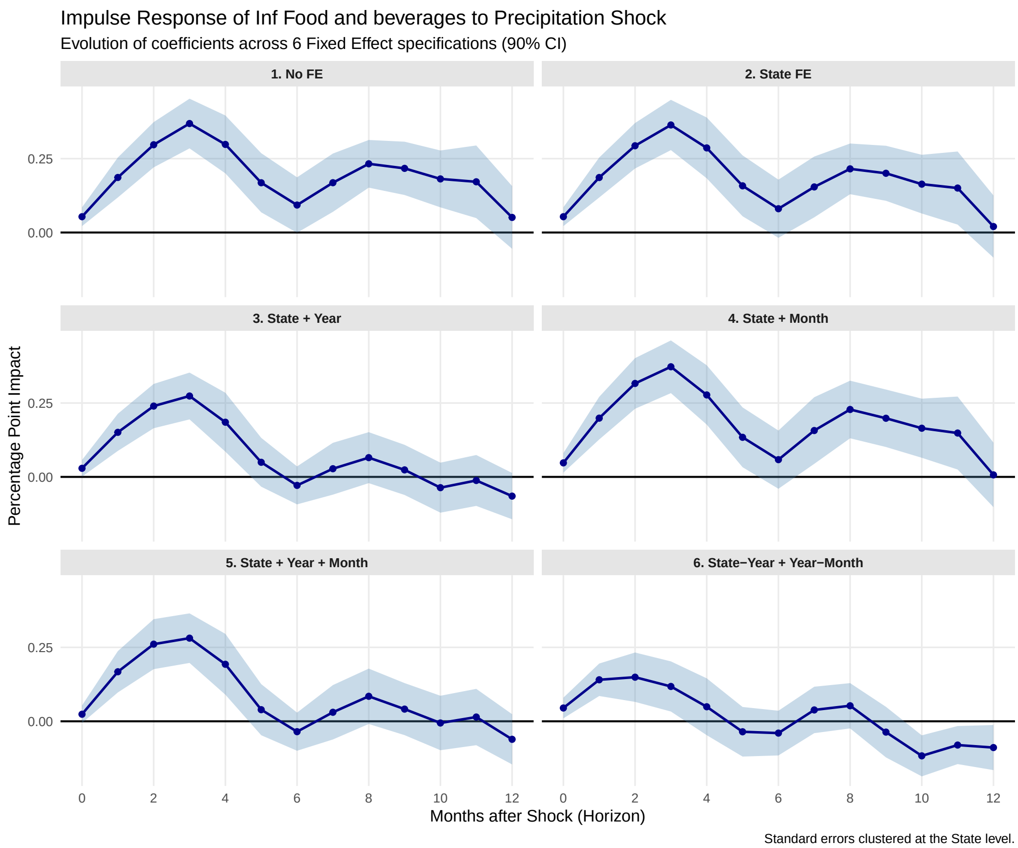


Figure 2: Local Projection Results for Food Inflation

Figure 2 traces the dynamic response of food and beverages inflation to precipitation shocks. Food inflation exhibits the strongest impact among all inflation components. With simple controls (panels 1-2), the peak impact occurs around month 3, reaching approximately 0.30 percentage points. Introducing state and year fixed effects (panel 3) reduces the effect, while adding calendar month fixed effects (panel 4) preserves a similar magnitude. The joint inclusion of state-year and year-month fixed effects (panel 6) continues to show some positive response in the initial months, though the effects become statistically insignificant in the later months. The persistence of some positive response even under stringent controls suggests that localized rainfall shocks do transmit to food prices.

## 7.3 Energy Inflation

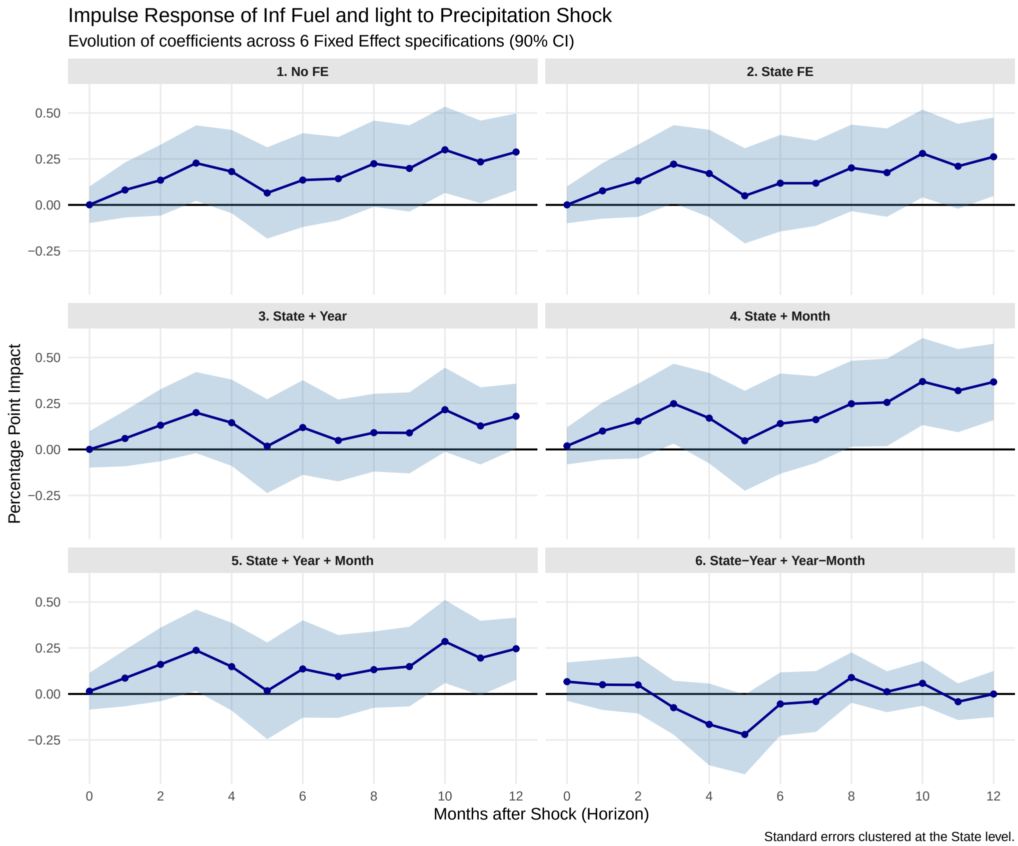


Figure 3: Local Projection Results for Energy Inflation

Figure 3 displays the impulse response of fuel and light inflation to precipitation shocks. In less restrictive specifications (panels 1-4), positive rainfall shocks appear to generate small positive effects on energy inflation, although statistically insignificant. However, the most restrictive specification with state-year and year-month fixed effects (panel 6) reveals near-zero and statistically insignificant effects. Comparing this with the positive responses observed for food inflation and suggests that energy prices in India are primarily driven by national and global fuel markets rather than localized climate shocks.

# 8 Heterogeneity Analysis

To better understand the underlying dynamics of these shocks, we perform a heterogeneity analysis across states with different economic levels.

## 8.1 Heterogeneity: Rich vs. Poor States

We further extend our analysis to examine whether precipitation shocks affect inflation differently in rich versus poor states. The economic intuition is that poorer states may be significantly more vulnerable to climate shocks due to a higher share of agricultural GDP (typically 20-30% compared to 10-15% in richer states), less diversified economies, weaker infrastructure and storage capacity, and lower household savings which necessitates immediate consumption responses. In contrast, richer states are potentially more insulated due to service and industry-dominated economies, superior market integration, and higher average incomes that allow for easier substitution across goods.

To test this, we classify states based on their Per Capita Net State Domestic Product (NSDP) relative to the National Average for the 2018-19 period, utilizing data from the Reserve Bank of India. We take 2018-2019 period as it is in the middle years of our analysis.

- **Rich States (15):** States with a per capita NSDP greater than or equal to the national average.
- **Poor States (14):** States with a per capita NSDP strictly less than the national average.

We introduce a binary indicator, $\text{Poor}_i$, and estimate the Local Projections model with an interaction term for each horizon $h$:

$$\begin{aligned}\pi_{i,t+h} = \lambda_{i,y}^{(h)} + \gamma_t^{(h)} + \beta_1^{(h)}\text{Precip\_Shock}_{i,t} + \beta_2^{(h)}(\text{Precip\_Shock}_{i,t} \times \text{Poor}_i) \\ + \beta_3^{(h)}\text{Temp\_Shock}_{i,t} + \sum_{l=1}^{2} \delta_l^{(h)} \pi_{i,t-l} \\ + \sum_{l=1}^{2} \theta_l^{(h)}\text{Precip\_Shock}_{i,t-l} + \sum_{l=1}^{2} \phi_l^{(h)}\text{Temp\_Shock}_{i,t-l} + \epsilon_{i,t+h}^{(h)}\end{aligned} \tag{4}$$

In this specification, $\beta_1^{(h)}$ captures the baseline impact of a precipitation shock on Rich States at horizon $h$. The aggregate impact on Poor States is represented by $(\beta_1^{(h)} + \beta_2^{(h)})$. The coefficient of interest is $\beta_2^{(h)}$, which explicitly measures the differential inflationary effect of a rainfall shock on poor states vis-a-vis rich states. Note that the standalone binary indicator for poor states ($\text{Poor}_i$) is perfectly absorbed by the state-year fixed effects ($\lambda_{i,y}^{(h)}$), hence it is not written in the extensive regression equation.

## 8.2 Heterogeneity Results: Rich vs. Poor

### 8.2.1 General Inflation

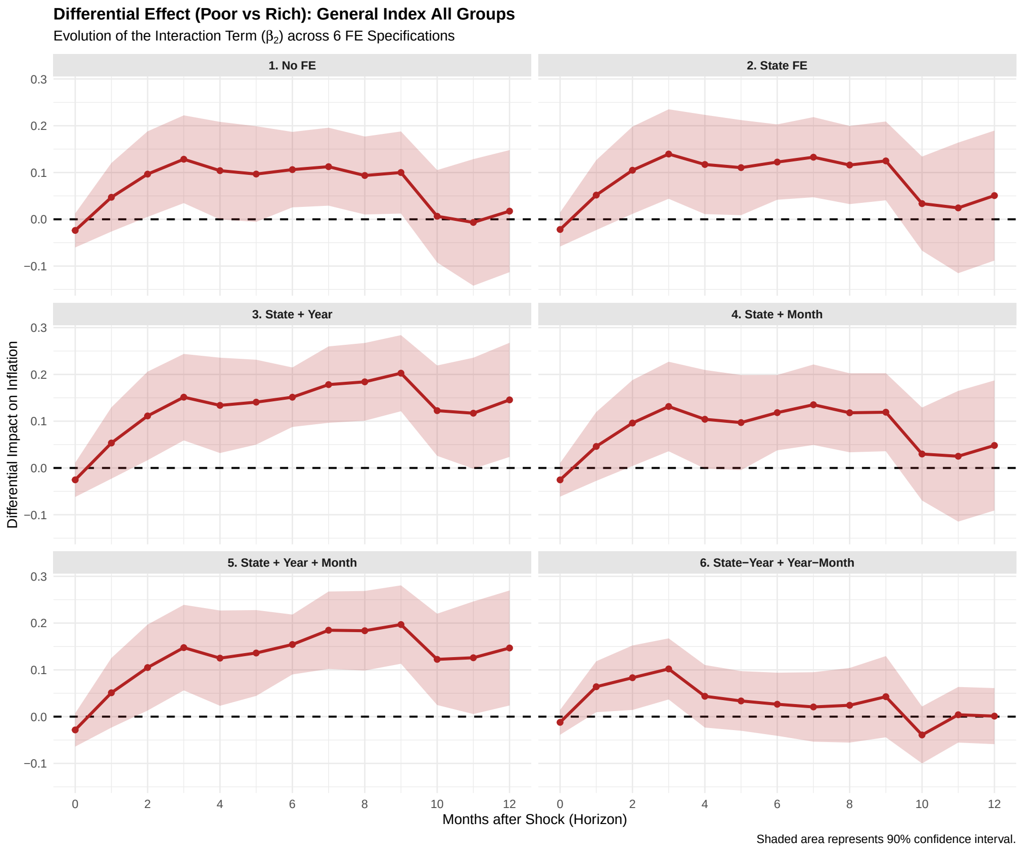


Figure 4: Heterogeneity Results for General Inflation: Rich vs. Poor States

Figure 4 presents the differential impact ($\beta_2$) of precipitation shocks on general inflation in poor states relative to rich states. Across specifications with no or minimal fixed effects (panels 1-2), the differential effect is positive and statistically significant for several horizons, suggesting that poor states experience larger inflationary impacts from rainfall shocks. The differential peaks around months 4-6 at approximately 0.10-0.15 percentage points. However, when state-year and year-month controls (panel 6) are introduced, the effect diminishes and becomes statistically across most horizons. This suggests that the effect in less restrictive models may be due to differences in state-specific economic policies and temporal trends.

### 8.2.2 Food Inflation

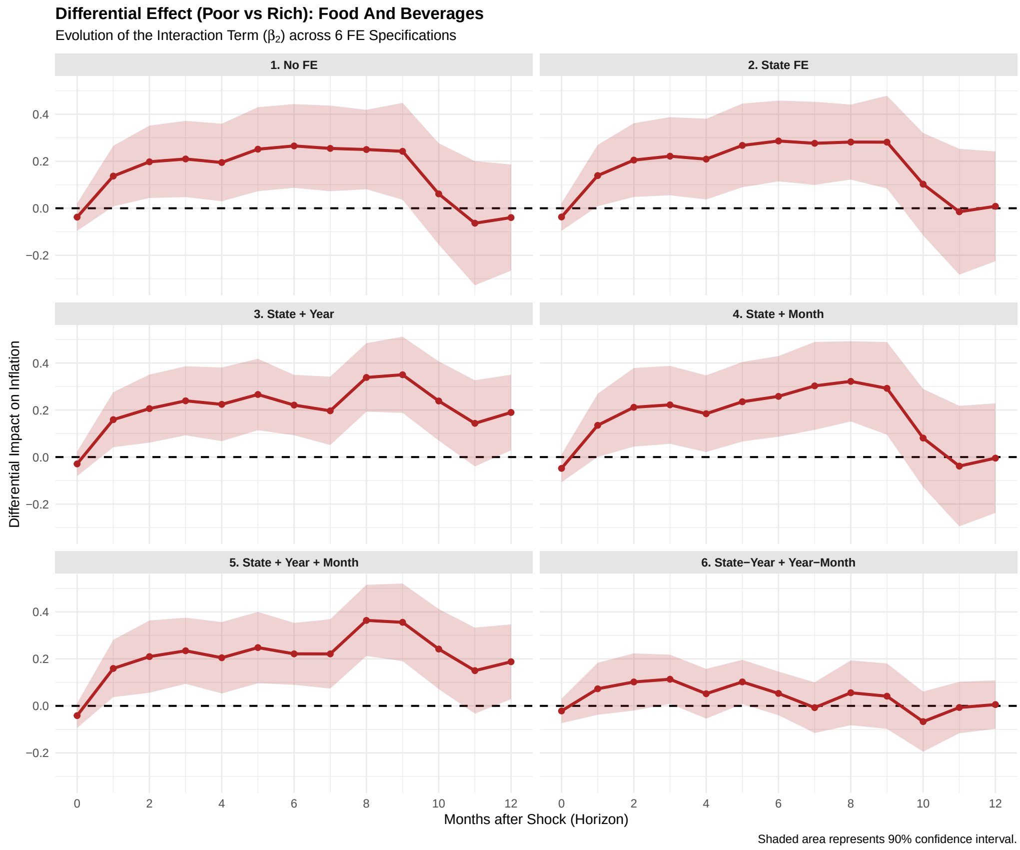


Figure 5: Heterogeneity Results for Food Inflation: Rich vs. Poor States

Figure 5 examines whether poor states exhibit disproportionate food inflation responses to precipitation shocks. In baseline specifications (panels 1-2), the interaction term is positive and reaches magnitudes of 0.20-0.30 percentage points around months 4-8, indicating that poor states experience substantially larger food price increases following adverse rainfall shocks. However, under the most restrictive specification with state-year and year-month fixed effects (panel 6), the differential effect statistically insignificant across all horizons.

### 8.2.3 Energy Inflation

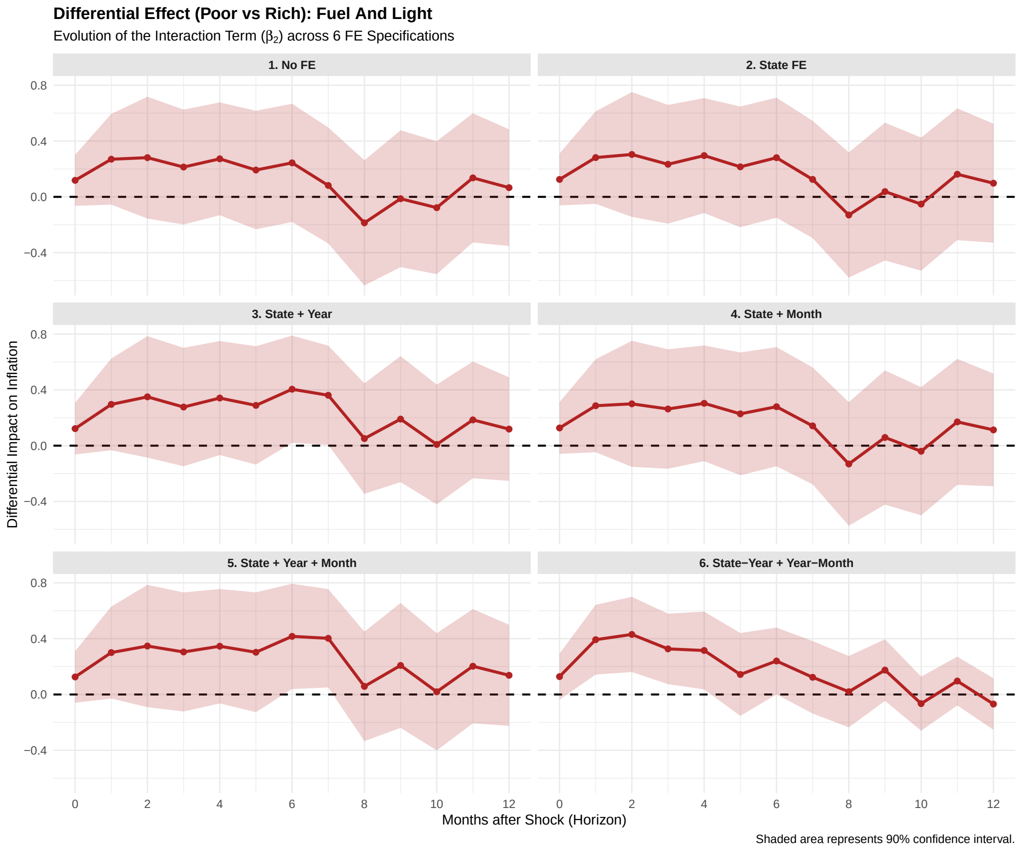


Figure 6: Heterogeneity Results for Energy Inflation: Rich vs. Poor States

Figure 6 investigates differential impacts on fuel and light inflation across state income levels. Across all specifications, the interaction term exhibits substantial volatility and remains statistically insignificant throughout the 12-month horizon. In less restrictive models (panels 1-4), the effect is statistically insignifcant. The most restrictive specification (panel 6) however shows a positive and statistically significant effect in the initial time horizons, which is a bit counterintuitive result. Hence, we can say that rainfall shocks do not differentially impact energy inflation for poor states compared to rich states.

# 9 Conclusion

This paper uses Local Projections to examine how precipitation and temperature shocks affect state-level inflation in India over the period 2014-2025. We find that the estimated impact of climate shocks on inflation depends critically on the econometric specification. In models with minimal controls, precipitation shocks appear to generate substantial inflationary pressures, particularly for food prices. However, when we introduce state-year and year-month fixed effects to control for state-specific trends and national macroeconomic shocks, these effects become much smaller or statistically insignificant. Food inflation shows the strongest sensitivity to climate shocks among all components, consistent with agricultural supply disruptions being the primary transmission channel, though even these effects are modest under more stringent specifications. Fuel and light inflation shows virtually no response to local precipitation shocks, suggesting energy prices are driven primarily by national and global factors. Our heterogeneity analysis reveals that poor states appear more vulnerable to climate shocks in baseline models, but this differential effect attenuates once we account for state-specific policies and economic trends. Overall, our findings suggest that localized climate shocks can affect general inflation and food prices in the short term. However, in the long-term (8-12 months), after accounting for robust fixed effects, there is a limited persistence of these rainfall shocks on inflation. For policymakers, this implies that short-term food price stabilization measures in the immediate aftermath of climate shocks are more critical than long-term inflation targeting adjustments, as the effects dissipate naturally within a year. Further study can focus on how distance from high agricultural production states affect inflation in the respective states in the face of weather shocks.

# A Appendix

# B Supplementary IRFs and Climate Maps

This appendix collects the result figures and climate maps that are not shown in the main text.

## B.1 Total-Impact IRFs from the Rich–Poor Specification

### B.1.1 General Inflation

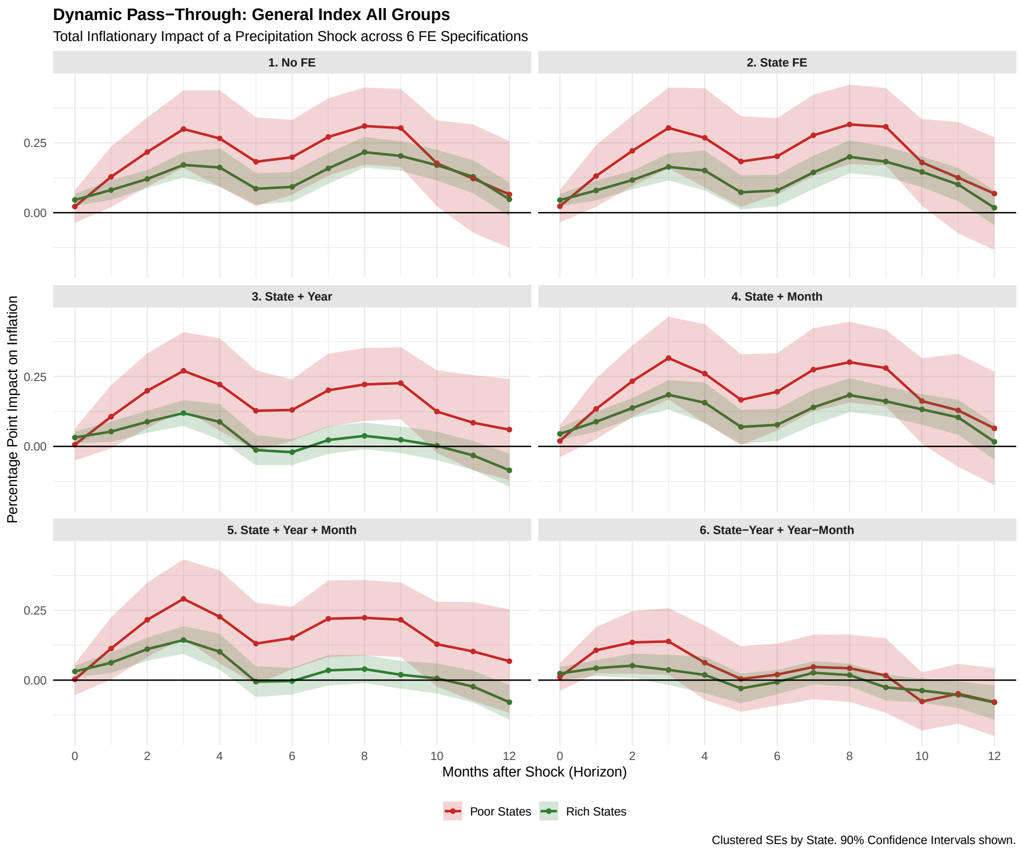


Figure 7: Supplementary total-impact IRFs for General Inflation.

### B.1.2 Food & Beverages Inflation

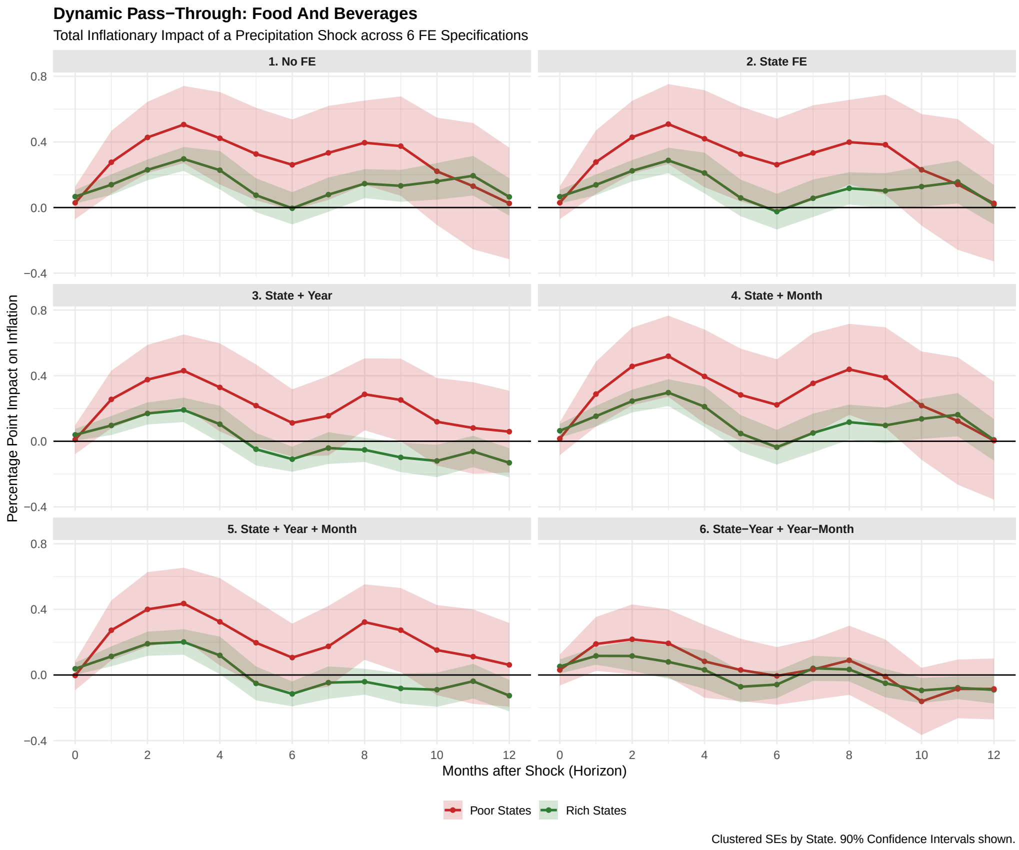


Figure 8: Supplementary total-impact IRFs for Food & Beverages Inflation.

### B.1.3 Fuel & Light Inflation

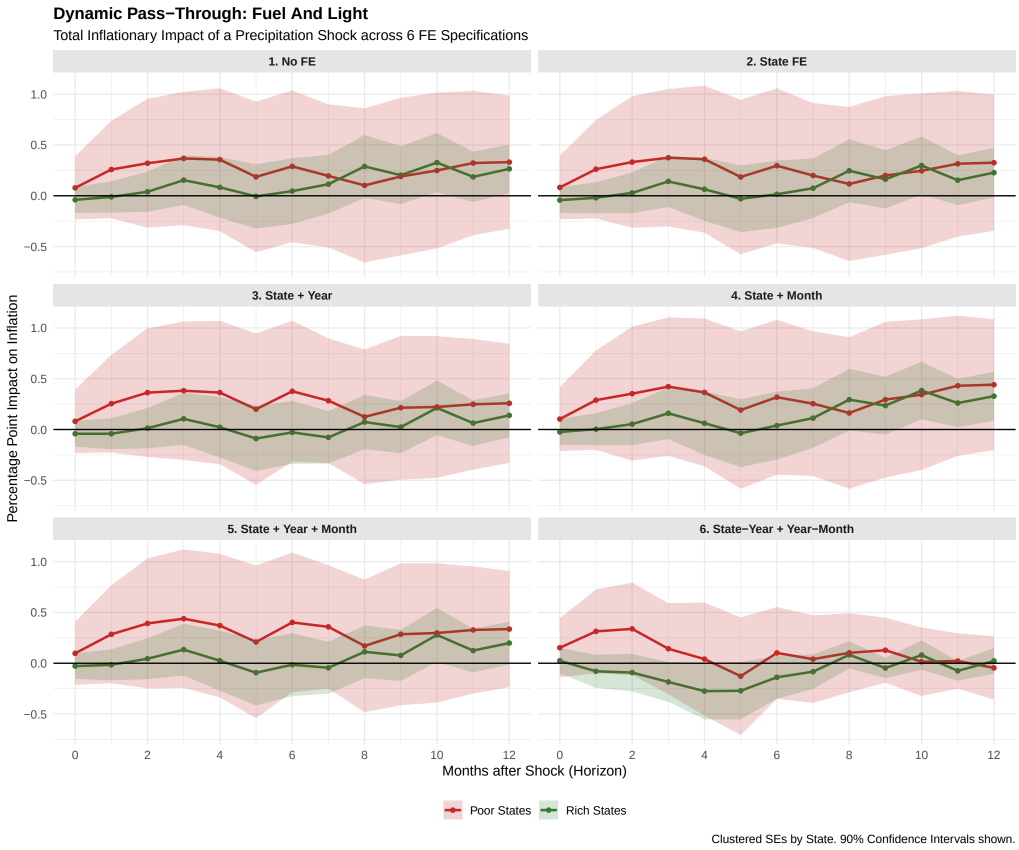


Figure 9: Supplementary total-impact IRFs for Fuel & Light Inflation.

## B.2 Supplementary Climate and Shock Maps

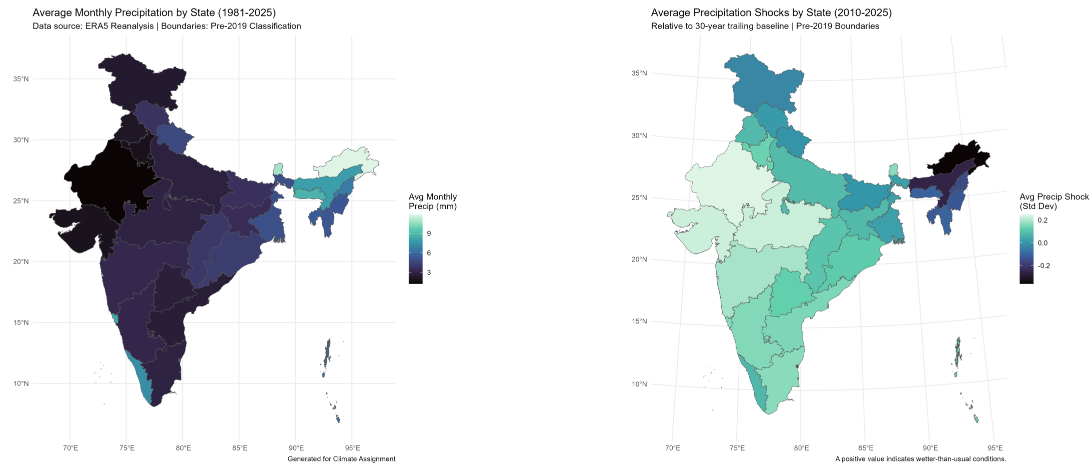


Figure 10: State-level precipitation levels (left) and precipitation shocks (right).

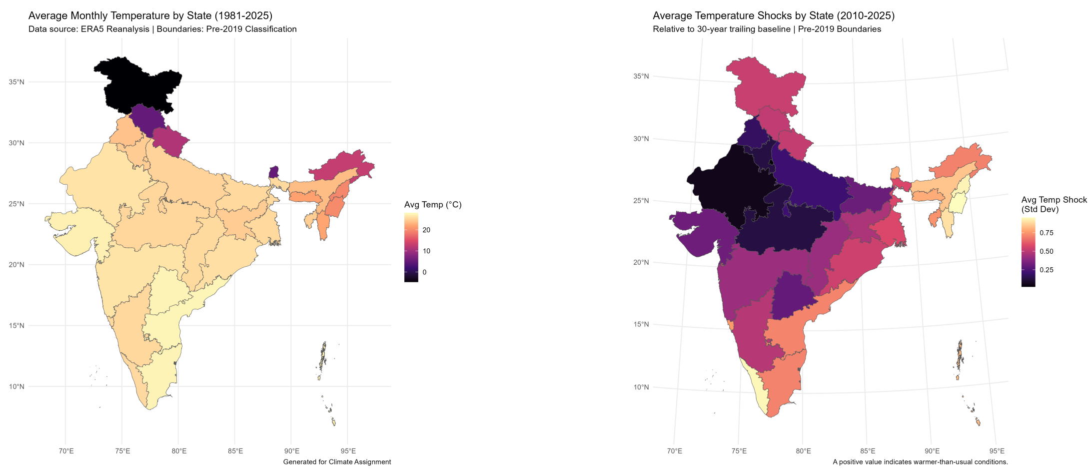


Figure 11: State-level temperature levels (left) and temperature shocks (right).

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