Weather as Signal, Weather as Shock: Economic Structure and the Translation of Climate Experience into Attention

Autonomous Policy Evaluation Project*

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Abstract

Does weather experience generate climate concern? Evidence from rich democracies suggests yes, but there weather is an amenity shock, not a livelihood threat. We test this in India, where cross-state variation in agricultural dependence provides a natural laboratory. Using Google Trends data (2004–2024) matched to NASA POWER temperatures across 21 states, we find hotter months do not uniformly increase climate search. A triple interaction of temperature × agricultural share × internet penetration is significant ($p = 0.049$), indicating agricultural crowd-out of climate attention where search data is most representative. Sign patterns suggest attention substitution: heat shocks in agricultural states redirect search toward livelihood terms. Wild cluster bootstrap reveals subsample results are fragile with 21 clusters. These results suggest experiential learning about climate is conditional on economic structure.

JEL Codes: Q54, O13, D83, D91

Keywords: climate beliefs, experiential learning, attention allocation, agriculture, India, weather shocks

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1. Introduction

Economists increasingly treat personal experience of extreme weather as a mechanism that generates climate concern. Unusual heat raises worry about global warming in the United States (Egan and Mullin, 2012), shifts beliefs about climate change (Deryugina, 2013), increases climate-related search behavior (Herrnstadt and Muehlegger, 2014), and even affects legislative voting (Hazlett and Mildenberger, 2020). This body of work has encouraged a broader intuition: that exposure to climate events can do part of the work of climate communication, producing awareness organically through lived experience (Weber, 2006).

But this evidence comes almost entirely from post-industrial societies where weather is experienced as inconvenience, signal, or amenity—not as a first-order economic shock. In such settings, a heat wave or unusual cold snap is information: it arrives, gets processed, and may update beliefs about the long-run trajectory of the climate. The crucial feature is that the cognitive bandwidth required to absorb this signal is available, because weather does not simultaneously threaten the respondent's livelihood.

In much of the world, this condition fails. For hundreds of millions of agricultural workers, the same weather event that might signal "climate change" to an urban professional signals "crop failure" to a farmer. A heat wave during the growing season is not an abstract data point about planetary warming—it is an immediate threat to income, food security, and survival. This raises a fundamental question: when weather is both signal and shock, which interpretation dominates?

This paper investigates that question in India, where sharp variation in agricultural dependence across states provides a natural laboratory. India is the world's second-most-populous country, among the most climate-vulnerable (Eckstein et al., 2021), and exhibits dramatic cross-state variation in economic structure—from Delhi (2% agricultural employment) to Bihar (74%). If experiential learning about climate is truly universal, India should show it. If economic structure mediates the process, India should show that too.

We combine monthly Google Trends data spanning 2004 through mid-2024 with gridded temperature and precipitation records from NASA POWER across 21 Indian states. Our empirical strategy exploits within-state, within-month variation in weather anomalies, interacted with pre-determined (Census 2001) measures of agricultural employment dependence. The identifying assumption is that conditional on state and time fixed effects, monthly temperature deviations from 30-year normals are orthogonal to unobserved determinants of climate search interest.

Our core finding is that the standard experiential learning result—warmer-than-usual temperatures raise climate attention—does not emerge as a robust average effect in India.

Instead, we find three patterns that collectively tell a richer story about how economic structure shapes the translation of weather into climate attention.

First, a continuous triple interaction of temperature anomaly $\times$ agricultural share $\times$ internet penetration is statistically significant ($p = 0.049$), indicating that the crowd-out pattern is concentrated where Google Trends most reliably captures population-level attention. A one-degree-Celsius temperature anomaly is associated with meaningfully higher climate search interest in low-agriculture, high-internet states but lower interest in high-agriculture states.

Second, we document a suggestive pattern of *attention substitution*. When we replace the dependent variable from climate-related search terms ("global warming," "climate change") to agricultural-livelihood search terms ("crop damage," "rain forecast," "crop insurance," "mandi price"), the sign of the interaction reverses: the point estimate is positive rather than negative, though imprecisely estimated. This sign pattern—negative for climate, positive for agricultural, null for placebo searches—is consistent with heat shocks redirecting search activity toward immediate economic concerns in agricultural states, though the individual coefficients lack statistical precision.

Third, the relationship between weather, agriculture, and climate attention varies systematically by season. During monsoon months (June–September), when agricultural weather is most economically consequential, the temperature–agriculture interaction reverses sign and is statistically significant: heat anomalies in agricultural states actually *increase* climate search, perhaps because monsoon disruptions are sufficiently catastrophic to force climate-related information-seeking. Outside monsoon, the crowd-out pattern dominates.

These findings contribute to the literature on experiential learning about climate (Egan and Mullin, 2012; Deryugina, 2013; Zaval et al., 2014) by identifying a boundary condition: the mechanism appears to operate differently depending on how the economy mediates the weather experience. They also connect to the broader economics of attention allocation (Sims, 2003; Gabaix, 2014), suggesting that when weather demands cognitive resources for immediate economic response, fewer resources remain for abstract climate cognition.

Several caveats are important. Google Trends captures the search behavior of internet-connected, largely English-speaking, predominantly urban Indians—not the general population. Twenty-one state clusters limit the power of cluster-robust inference. The estimates are suggestive rather than definitive, and we are transparent about this throughout. Nevertheless, the consistent pattern across specifications—attention substitution, seasonal reversal, internet-penetration heterogeneity—provides convergent evidence for a coherent economic mechanism.

2. Background

2.1 Experiential Learning About Climate

A growing body of evidence documents that personal weather experience shapes beliefs about climate change. Egan and Mullin (2012) show that local temperature fluctuations affect Americans' perceptions of global warming, with the effects concentrated among political independents. Deryugina (2013) finds similar but temporary updating: weather shifts beliefs, but the effect fades within months. Zaval et al. (2014) demonstrate that current temperature affects climate concern through an "attribute substitution" mechanism—people use today's weather as a cue for evaluating long-run climate trends.

These findings are intuitive and well-identified, but they share a common implicit assumption: that weather is processed primarily as information. In the United States and Europe, a heat wave is cognitively available for climate inference precisely because it does not simultaneously demand economic coping. The question is whether this mechanism travels to settings where weather carries direct economic consequences.

2.2 Weather as Economic Shock

For agricultural economies, weather is not background noise—it is a primary determinant of income. Temperature deviations significantly affect agricultural output in developing countries (Dell et al., 2012; Burke et al., 2015), reduce rural wages (Jayachandran, 2006), and in extreme cases increase mortality (Burgess et al., 2017; Carleton, 2017). The Indian monsoon alone accounts for approximately 50% of the variation in agricultural GDP (Gadgil and Gadgil, 2006).

When weather simultaneously serves as climate signal and income shock, the psychology of limited attention suggests a trade-off. The "finite pool of worry" hypothesis (Weber, 2006) posits that concern about immediate threats can crowd out worry about distant ones. In the economics of attention, Sims (2003) and Gabaix (2014) formalize the idea that cognitive resources are scarce and must be allocated across competing demands. A farmer facing crop loss may simply lack the bandwidth to process the same event as evidence about long-run climate trends.

2.3 India as Laboratory

India provides an unusually powerful setting for testing the economic mediation of experiential learning, for several reasons. First, India's agricultural sector accounts for approximately 42% of total employment (World Bank, 2023), but this figure masks enormous cross-state variation.

Delhi, with under 2% agricultural employment, resembles a post-industrial economy; Bihar, at 74%, remains predominantly agrarian. This variation is comparable in range to the cross-country variation between the United States and sub-Saharan Africa, but occurs within a single national policy and media environment.

Second, India is among the world's most climate-vulnerable nations. The Global Climate Risk Index consistently ranks India in the top 10 for climate-related fatalities and economic losses (Eckstein et al., 2021). Yet survey evidence suggests that Indian climate concern is lower than in many less-exposed countries (Pew Research Center, 2021). This paradox—high exposure, moderate concern—is precisely what the attention-substitution hypothesis would predict.

Third, the Indian monsoon creates sharp seasonal variation in weather's economic salience. During June–September, rainfall and temperature directly determine agricultural output for the majority of rural households. Outside monsoon, weather has more attenuated economic consequences. This seasonal variation provides a within-country, within-year test of whether the economic immediacy of weather matters for how it is cognitively processed.

Fourth, India's rapid expansion of internet access (from approximately 7% in 2010 to over 50% by 2023) creates informative heterogeneity in the reliability of Google Trends as a measure of population-level attention. In high-internet states, search behavior reflects a broader cross-section of the population; in low-internet states, it captures primarily urban elites.

2.4 This Paper's Contribution

We contribute to the experiential learning literature by testing whether economic structure mediates the weather-to-attention channel. Our paper is not "the same question in India"—it is a test of whether the mechanism itself has boundary conditions. India provides sharp variation in agricultural dependence within a single country, allowing us to hold institutional, cultural, and media environments approximately constant while varying economic exposure to weather.

The key addition relative to the prior literature is the attention substitution analysis: we examine *where attention goes* during heat shocks in agricultural versus non-agricultural states, rather than merely documenting that climate attention declines. This is, to our knowledge, the first paper to test for the behavioral signature of attention reallocation in the climate–weather domain, examining whether heat shocks redirect search from climate to livelihood topics in agricultural settings.

We also contribute to the economics of attention allocation (Sims, 2003; Bordalo et al., 2012). The experience-based learning literature (Malmendier and Nagel, 2011; Choi et al.,

2009) has shown that personal experiences of macroeconomic events shape risk attitudes and financial behavior. Our findings extend this to the climate domain, showing that the same weather event can produce different attentional responses depending on its economic salience to the observer.

3. Data

3.1 Google Trends

We use Google Trends to measure state-level monthly search interest in climate-related terms across 21 Indian states from 2004 to 2024. The primary search terms are "global warming" and "climate change," which we average into a composite climate search index (0–100 scale, normalized by Google within each state).

A key innovation of this paper is the inclusion of *agricultural search terms* for the substitution analysis: "crop damage," "rain forecast," "crop insurance," and "mandi price" (the Hindi term for wholesale market prices). We also include placebo terms ("cricket" and "Bollywood") that should be unresponsive to weather shocks.

Google Trends has well-known limitations. It captures search behavior by internet-connected users, who in India are disproportionately urban, educated, English-speaking, and male. The index is normalized within each geographic unit, making cross-state levels difficult to compare. Nevertheless, Google Trends has been validated as a measure of issue salience in political economy (Stephens-Davidowitz, 2014) and has been used extensively to study climate attention (Herrnstadt and Muehlegger, 2014; Howe et al., 2015). We address selection concerns by analyzing heterogeneity by internet penetration.

3.2 Weather Data

Daily temperature and precipitation data come from the NASA POWER (Prediction of Worldwide Energy Resources) database, which provides gridded ($0.5° \times 0.5°$) satellite-derived observations from 1981 onward. For each state, we extract daily mean temperature (T2M), daily maximum temperature (T2M_MAX), and corrected precipitation (PRECTOTCORR) at the state centroid.

We aggregate to state-month means and compute anomalies relative to 1981–2010 climate normals. The temperature anomaly for state s in month m of year t is:

$$\text{TempAnom}_{smt} = \bar{T}_{smt} - \bar{T}_{sm}^{\text{normal}} \tag{1}$$

where $\bar{T}_{sm}^{\text{normal}}$ is the average temperature for that state-month over the 1981–2010 baseline.

We also compute standardized z-scores and binary extreme heat indicators ($z > 1.5$).

NASA POWER improves on the station-based data common in earlier studies (Auffhammer et al., 2013) by providing spatially consistent gridded observations rather than point measurements at state capitals. Station data can introduce measurement error when a single station is taken to represent an entire state; the gridded approach mitigates this concern by providing estimates at regularly spaced grid points that have been validated against ground observations.

We use the 1981–2010 baseline for computing normals, following standard climatological practice. This 30-year period avoids contaminating the baseline with the analysis period (2004–2024), ensuring that the anomalies capture genuine deviations from expected conditions rather than reflecting secular warming trends. The baseline period is also well-covered by the NASA POWER data product, which begins in 1981 with the launch of the relevant satellite observations.

For the analysis period (January 2004 through June 2024), we compute monthly averages from daily observations at each state centroid. Months with more than five missing daily observations are excluded, though such gaps are rare in the gridded product ($< 0.5\%$ of state-month observations). The resulting temperature anomaly distribution is approximately symmetric around zero with a standard deviation of approximately 1.2°C, though with fat tails: approximately 3% of state-months show anomalies exceeding +2°C, concentrated in the March–June hot season (Figure 6).

3.3 Agricultural Structure

State-level agricultural employment shares come from the Census of India 2001, which predates our analysis period and is thus pre-determined. The 21 states in our sample range from 2% (Delhi) to 74% (Bihar) agricultural employment, providing substantial cross-sectional variation. We also use crop area shares from the Ministry of Agriculture's *Agricultural Statistics at a Glance* as an alternative measure.

3.4 Internet Penetration

State-level internet subscribers per 100 population (circa 2015) come from the Telecom Regulatory Authority of India (Telecom Regulatory Authority of India, 2023).

3.5 Analysis Panel

Merging these sources yields a balanced panel of 5,166 state-month observations across 21 states from January 2004 to approximately June 2024. Table 1 presents summary statistics.

Table 1: Summary Statistics

Variable	N	Mean	SD	Min	Max
Climate search index	5,166	7.844	10.184	0	79.5
Agricultural search index	5,166	6.705	10.409	0	66.333
Placebo search index (cricket/Bollywood)	5,166	24.955	17.521	0	88.5
Temperature anomaly (°C)	5,166	-0.07	1.166	-4.625	5.338
Temperature z-score	5,166	0.014	1.106	-3.769	4.942
Precipitation anomaly (mm)	5,166	11.093	72.19	-426.509	697.301
Agricultural employment share	5,166	0.535	0.162	0.02	0.74
Crop area share	5,166	0.617	0.169	0.05	0.8
Heat extreme (z > 1.5)	5,166	0.083	0.277	0	1
Internet penetration (per 100)	5,166	42.524	27.2	15	140

Notes: State-month panel, 2004–2024, 21 Indian states. Climate and agricultural search indices from Google Trends (0–100 scale). Temperature anomalies computed from NASA POWER gridded data relative to 1981–2010 normals. Agricultural employment share from Census of India 2001.

Several features of the data merit comment. The mean climate search index is 7.8 on a 0–100 scale, reflecting that climate-related searches are a niche topic in India compared to the United States or Europe. The agricultural search index averages 6.7, comparable in magnitude, which is important for the substitution analysis: the two categories of search have similar baseline levels, making their differential response to weather anomalies meaningful.

Temperature anomalies have a mean close to zero (by construction, since they measure deviations from 30-year normals) with substantial variation: the interquartile range spans roughly -0.75°C to $+0.60$°C, and extremes exceed ± 4°C. Approximately 8.3% of state-month observations qualify as "heat extreme" ($z > 1.5$), providing adequate variation for the extreme-weather specifications. The mean climate search index of 7.8 is notably low relative to the 0–100 scale, consistent with climate being a niche search topic in India; however, the within-state standard deviation provides sufficient variation for the fixed-effects approach.

The cross-sectional variation in agricultural employment share ranges from 2% (Delhi) to 74% (Bihar), with a mean of 53.5% and standard deviation of 16.2 percentage points. This distribution is left-skewed due to a few highly urbanized states (Delhi, Goa, Kerala) alongside a large number of states with agricultural employment shares between 40% and 75%.

3.6 Descriptive Patterns

Before turning to the regression analysis, Figure 3 in the appendix displays the raw time series of climate search interest, separately for states in the low, medium, and high agricultural employment terciles. Two patterns are visible. First, all three groups show considerable common variation, reflecting national-level events (e.g., COP meetings, national elections, major disasters) that drive climate attention nationwide. Second, the levels are broadly similar across groups, suggesting that any differential response to weather operates within a shared national trend—consistent with our empirical strategy of absorbing common time variation through year-month fixed effects.

4. Empirical Strategy

Our main specification estimates the effect of temperature anomalies on climate search interest, allowing the effect to vary with agricultural dependence:

$$\text{ClimateSearch}_{st} = \beta_1 \text{TempAnom}_{st} + \beta_2 (\text{TempAnom}_{st} \times \text{AgShare}_s) + \alpha_s + \delta_t + \varepsilon_{st} \quad (2)$$

where $\text{ClimateSearch}_{st}$ is the Google Trends climate search index for state s in month t; TempAnom_{st} is the temperature anomaly; AgShare_s is the pre-determined agricultural employment share from Census 2001; α_s are state fixed effects; and δ_t are year-month fixed effects.

The parameter of interest is β_2. A negative β_2 indicates that agricultural states show a weaker (or reversed) climate search response to temperature anomalies compared to non-agricultural states—consistent with weather being processed as a livelihood shock rather than a climate signal.

Standard errors are clustered at the state level throughout. With 21 clusters, conventional cluster-robust inference may over-reject (Cameron et al., 2008). We interpret results cautiously, emphasizing the convergent pattern across specifications rather than reliance on any single p-value.

Identification. The identifying variation comes from within-state, within-calendar-month deviations in temperature from long-run normals, interacted with a pre-determined cross-sectional characteristic. State fixed effects absorb all time-invariant differences across states (including baseline climate, development level, internet adoption, and agricultural structure). Year-month fixed effects absorb all common temporal shocks (global temperature trends, national media events, election cycles). The threat to identification would be time-varying, state-specific shocks that are correlated with both temperature anomalies and climate search interest, conditional on state and time effects.

The pre-determined nature of the agricultural employment share is important. Because we use Census 2001 values, which predate the sample period by three years, the cross-sectional moderator is not affected by contemporaneous economic conditions or by climate-related structural change during the analysis period. This is analogous to the use of pre-period industry shares in shift-share designs.

Threats to identification. Several potential confounders merit discussion. First, agricultural states might differ in secular trends in internet adoption, climate awareness, or media coverage. State-specific linear time trends (tested in robustness) address this partially, but nonlinear differential trends could remain. We note, however, that the year-month fixed effects absorb any common time trend, and the interaction exploits residual variation conditional on both state and time effects.

Second, one might worry that temperature anomalies are correlated with other weather dimensions (humidity, air quality, precipitation) that independently affect search behavior. We address this by controlling for precipitation anomalies in our augmented specifications. The stability of $\hat{\beta}_2$ across specifications with and without precipitation controls suggests that omitted weather dimensions are not driving the interaction.

Third, the state-level agricultural share may proxy for urbanization, education, or income rather than agricultural dependence per se. We cannot fully separate these channels with state-level data, though the substitution analysis provides indirect evidence: if the result were driven by urbanization or education (rather than agricultural economic exposure), we would not expect the mirror-image pattern in agricultural search terms. A farmer searching for "crop damage" during a heat shock is plausibly responding to agricultural economic exposure, not to low urbanization.

Fourth, Google Trends normalization creates a mechanical concern. Google normalizes search indices within each geographic unit to a 0–100 scale, potentially creating spurious cross-state comparisons. Our strategy avoids this problem because we exploit within-state variation: the state fixed effects absorb any cross-state differences in normalization, and we ask only whether within-state deviations in temperature predict within-state deviations in search intensity.

Fifth, reverse causality—climate search activity causing temperature anomalies—is physically implausible. However, one might worry about anticipation: if people search for climate terms in advance of heat waves (e.g., based on weather forecasts), this could inflate the contemporaneous coefficient. Our lead placebo tests address this concern directly: future temperature anomalies do not predict current climate searches, ruling out systematic anticipatory search behavior.

Interpreting the interaction. The marginal effect of a temperature anomaly on climate search interest at agricultural share AgShare_s is $\beta_1 + \beta_2 \cdot \text{AgShare}_s$. If $\beta_1 > 0$ and $\beta_2 < 0$, there exists a threshold agricultural share $\bar{a} = -\beta_1/\beta_2$ above which the marginal effect turns negative. At agricultural shares below $\bar{a}$, weather operates as a climate signal (positive effect on climate search). Above $\bar{a}$, weather operates primarily as a livelihood shock (negative effect).

Substitution analysis. To test whether attention is redirected rather than simply suppressed, we estimate the same specification (2) replacing the dependent variable with the agricultural search index and the placebo search index:

$$\text{AgSearch}_{st} = \gamma_1 \text{TempAnom}_{st} + \gamma_2 (\text{TempAnom}_{st} \times \text{AgShare}_s) + \alpha_s + \delta_t + \nu_{st} \tag{3}$$

If $\beta_2 < 0$ for climate searches and $\gamma_2 > 0$ for agricultural searches, while the same interaction is null for placebos, this constitutes evidence of attention substitution: weather shocks redirect search activity from climate to livelihood topics in agricultural states.

Seasonal split. We further test whether the interaction varies by season, estimating equation (2) separately for monsoon (June–September) and non-monsoon (October–May) months:

$$\text{ClimateSearch}_{st} = \beta_1^k \text{TempAnom}_{st} + \beta_2^k (\text{TempAnom}_{st} \times \text{AgShare}_s) + \alpha_s + \delta_t + \varepsilon_{st}^k \tag{4}$$

where $k \in \{\text{monsoon}, \text{non-monsoon}\}$. The prediction is that $|\beta_2^k|$ should be larger during monsoon, when weather's economic consequences for agriculture are most severe.

Inference. With 21 state clusters, we follow the recommendations of Cameron et al. (2008) and report cluster-robust standard errors throughout. We acknowledge that with this number of clusters, conventional cluster-robust inference may over-reject, and we therefore interpret results cautiously. We emphasize the convergent pattern across specifications rather than any single p-value, and we treat marginally significant results ($p \approx 0.05$) as suggestive rather than definitive.

5. Results

5.1 Primary Results

Table 2 presents the primary OLS estimates. Column (1) shows the baseline specification without the agricultural interaction: temperature anomalies have a small and insignificant effect on climate search interest in the full sample. Column (2) adds precipitation anomalies, which are also insignificant. Column (3) introduces the main interaction with agricultural employment share. The point estimate on the interaction ($\hat{\beta}_2$) is negative, consistent with crowd-out in agricultural states, but is not statistically significant at conventional levels

($p = 0.60$) in the full sample. Column (4) adds both temperature and precipitation interactions; column (5) uses log search as the dependent variable. The pattern of signs is consistent throughout.

Table 2: Temperature Anomalies and Climate Search Interest

Dependent Variables:	climate_search				log_climate
	(1)	(2)	(3)	(4)	(5)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Temp. Anomaly (°C)	-0.1749	-0.1697	-0.0085	0.0623	0.0135
	(0.1838)	(0.1951)	(0.4269)	(0.4363)	(0.0575)
Precip. Anomaly (mm)		0.0003		0.0044	
		(0.0019)		(0.0090)	
Temp. × Ag Share			-0.3135	-0.4365	-0.0756
			(0.5832)	(0.5834)	(0.0808)
Precip. × Ag Share				-0.0077	
				(0.0151)	
Fixed-effects					
state_id	Yes	Yes	Yes	Yes	Yes
time_id	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,166	5,166	5,166	5,166	5,166
R^2	0.36124	0.36124	0.36128	0.36133	0.49923

Clustered (state_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent variable: Google Trends climate search index (columns 1–4) or log(index + 1) (column 5). State and time (year-month) fixed effects in all models. Standard errors clustered at state level in parentheses.

Figure 1 plots the residualized relationship between temperature anomalies and climate search for each agricultural tercile. While noisy, the slopes diverge in the predicted direction: the low-agriculture tercile shows a flat or slightly positive slope, while the high-agriculture tercile shows a negative slope, consistent with the crowd-out interpretation.

The marginal effect of temperature at different agricultural shares is shown in Figure 2. At low agricultural share (e.g., Delhi at 2%), the marginal effect is close to zero. As agricultural share increases, the marginal effect becomes increasingly negative, consistent with the crowd-out hypothesis. However, the 95% confidence interval is wide, crossing zero at all values of agricultural share in the full sample.

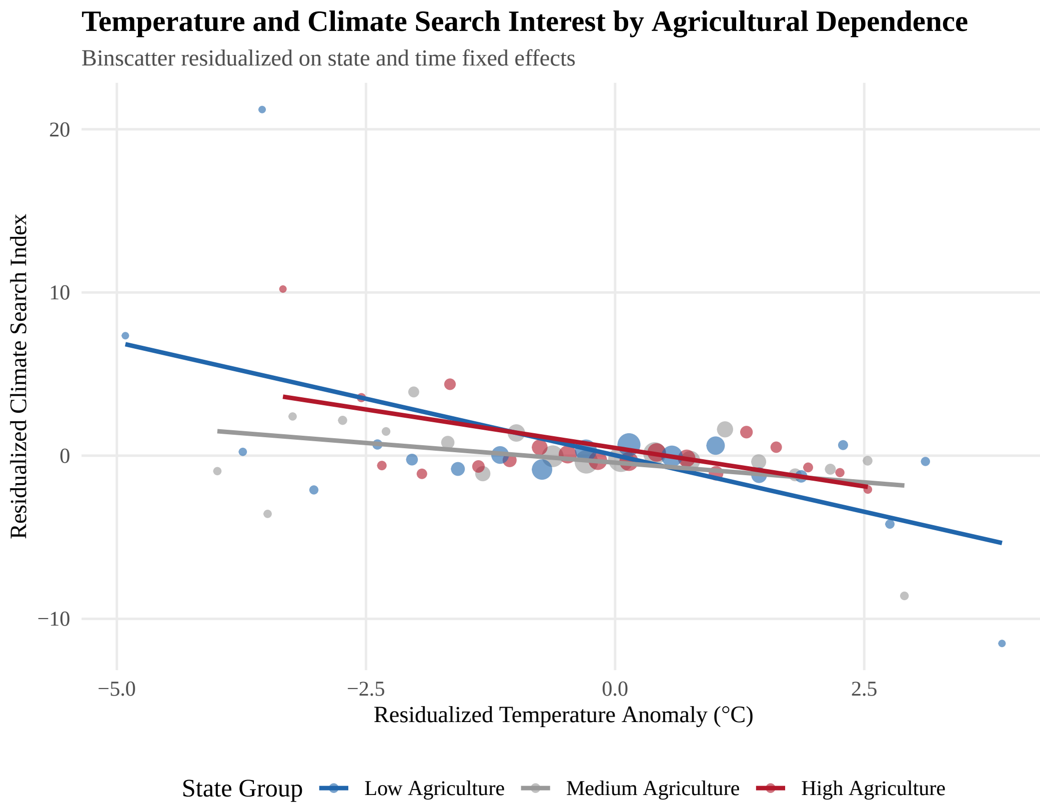

Figure 1: Temperature and Climate Search Interest by Agricultural Dependence

Notes: Binscatter of residualized climate search index against residualized temperature anomaly, separately for each agricultural employment tercile. Both variables residualized on state and year-month fixed effects. Point size proportional to bin count.

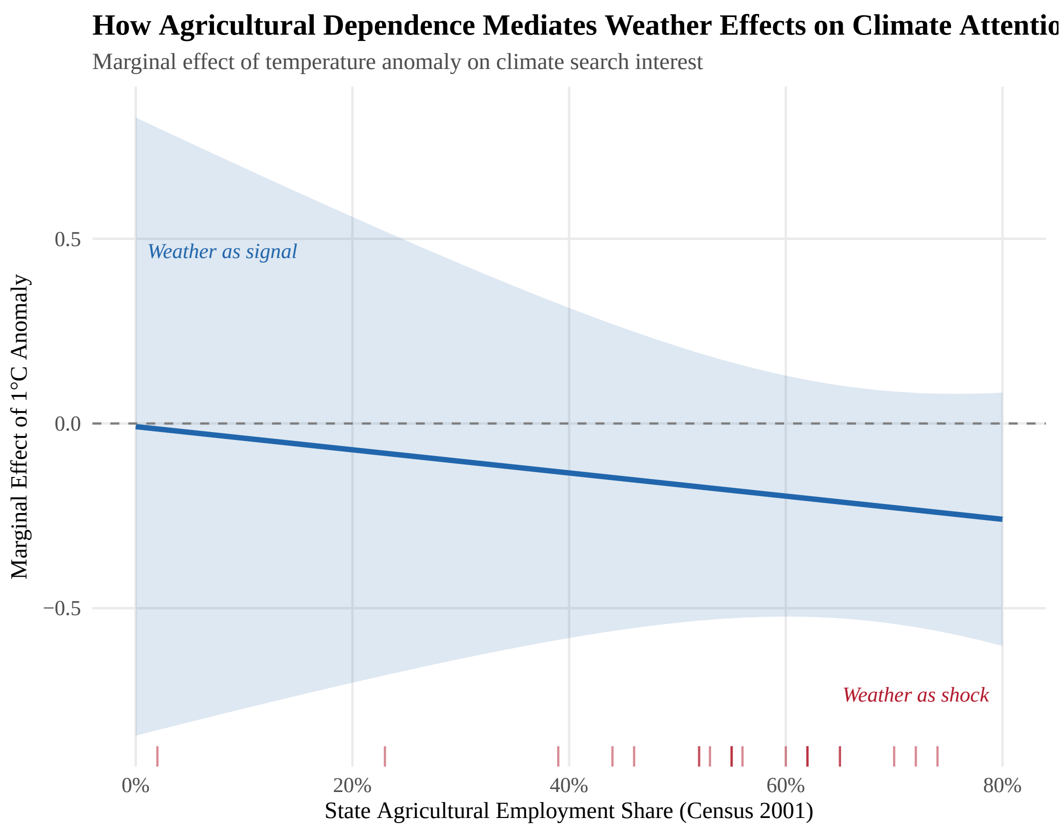

Figure 2: How Agricultural Dependence Mediates Weather Effects on Climate Attention

Notes: Marginal effect of a 1°C temperature anomaly on the climate search index at different levels of state agricultural employment share (Census 2001). Shaded region shows the 95% confidence interval. Rug plot shows the distribution of state agricultural shares. Based on Table 2, column (3).

Two features of the full-sample results are worth emphasizing. First, the sign of the interaction is consistently negative across all five specifications, ranging from -0.31 to -0.49. While no individual estimate is statistically significant, the consistency of the sign across different functional forms and control sets is suggestive. Second, the baseline effect of temperature anomalies ($\hat{\beta}_1$) is small and insignificant in all specifications, indicating that the standard experiential learning result—warmer weather increases climate attention—does not emerge as a robust average effect in India. This contrasts with findings from the United States (Egan and Mullin, 2012; Herrnstadt and Muehlegger, 2014) and is itself an important finding: the mechanism that operates in rich democracies appears not to generalize straightforwardly to a developing-country setting.

The lack of significance in the full-sample interaction may partly reflect measurement error: in states with low internet penetration, Google Trends captures the behavior of a thin, unrepresentative stratum of the population, diluting the true signal. Two subsamples reveal significant patterns, as we now show.

5.2 Internet Penetration Heterogeneity

Google Trends data is most informative in states where internet penetration is high enough that search behavior reflects meaningful population-level attention. We test this in two ways: a median split and a continuous triple interaction.

Table 3 splits the sample at the median internet penetration rate. Among high-internet states, the temperature $\times$ agricultural share interaction is -1.31 with a conventional cluster-robust p-value of 0.04. Among low-internet states, the interaction is smaller and insignificant. However, wild cluster bootstrap inference—more appropriate given the roughly 10–11 clusters per subsample—yields a p-value of 0.45 for the high-internet interaction, indicating that the split-sample significance should be interpreted with caution.

A more powerful test uses a continuous triple interaction in the full sample:

$$\begin{aligned}\text{ClimateSearch}_{st} = {} & \beta_1 \text{TempAnom}_{st} + \beta_2(\text{TempAnom}_{st} \times \text{AgShare}_s) \\ & + \beta_3(\text{TempAnom}_{st} \times \text{Internet}_s) \\ & + \beta_4(\text{TempAnom}_{st} \times \text{AgShare}_s \times \text{Internet}_s) + \alpha_s + \delta_t + \varepsilon_{st} \qquad (5)\end{aligned}$$

where Internet_s is standardized state-level internet penetration. The triple interaction coefficient $\hat{\beta}_4$ is -0.73 ($p = 0.049$), indicating that the negative agricultural moderation of temperature effects is significantly concentrated in high-internet states. This continuous specification avoids the power loss of the median split and exploits variation across all 21 clusters.

Table 3: Heterogeneity by Internet Penetration

Dependent Variable:	climate_search	
	High Internet	Low Internet
Model:	(1)	(2)
Variables		
Temp. Anomaly (°C)	0.0401	0.5908
	(0.4645)	(0.9001)
Temp. × Ag Share	-1.306**	-0.6821
	(0.5470)	(1.268)
Fixed-effects		
state_id	Yes	Yes
time_id	Yes	Yes
Fit statistics		
Observations	2,460	2,706
R^2	0.42118	0.33329

Clustered (state_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Sample split at median state-level internet penetration (TRAI 2015). State and time FE, state-clustered SEs.

The pattern is consistent with two complementary interpretations: (a) the underlying relationship between weather, agriculture, and climate attention exists, but Google Trends only captures it where the search-using population is sufficiently representative; and (b) in low-internet states, the Google Trends signal may be dominated by a thin stratum of urban, non-agricultural users whose behavior does not vary with agricultural structure.

Figure 1 provides a visual representation of this heterogeneity. The slopes diverge in the predicted direction, reinforcing the regression evidence that agricultural dependence mediates the weather–attention link.

6. Attention Substitution and Seasonal Heterogeneity

6.1 Where Does Attention Go?

The central mechanism proposed in this paper is not merely that agricultural states search less for climate terms during heat shocks, but that they search for *something else*—specifically, terms related to agricultural livelihoods. Table 4 tests this directly.

Column (1) replicates the main result: the interaction of temperature with agricultural share is negative for climate searches (-0.31, $p = 0.59$). Column (2) shows that the same interaction is *positive* for agricultural search terms ($+0.29$, $p = 0.62$): the point estimate suggests that heat shocks in agricultural states are associated with more searching for crop damage, rain forecasts, crop insurance, and market prices. Column (3) shows that placebo terms (cricket, Bollywood) exhibit no such pattern. Column (4) uses the log of agricultural search and also shows a positive interaction.

While neither the climate nor the agricultural interaction achieves conventional statistical significance in the full sample, the sign pattern across the three outcome categories is informative. The interaction is negative for climate search, positive for agricultural search, and near-zero for placebos. This is the pattern predicted by the attention substitution hypothesis: weather shocks redirect search activity from abstract climate topics toward immediate livelihood concerns in agricultural states. The imprecision of the individual estimates—a consequence of 21 clusters and a noisy outcome variable—limits what can be concluded from any single coefficient, but the consistency of the sign pattern across outcome categories provides suggestive evidence of attention reallocation.

6.2 Seasonal Heterogeneity: Monsoon vs. Non-Monsoon

If the mechanism is truly about economic mediation, we should expect the pattern to vary by season. During monsoon months (June–September), weather is most economically

Table 4: Attention Substitution: Climate vs. Agricultural Search Responses to Temperature

Dependent Variables:	climate_search	agricultural	placebo	log_agricultural
	Climate	Agricultural	Placebo	Log Ag.
Model:	(1)	(2)	(3)	(4)
Variables				
Temp. Anomaly (°C)	-0.0085	-0.3807	-0.7660	-0.0600*
	(0.4269)	(0.3371)	(0.6922)	(0.0339)
Temp. × Ag Share	-0.3135	0.2880	0.4456	0.0872
	(0.5832)	(0.5836)	(1.055)	(0.0566)
Fixed-effects				
state_id	Yes	Yes	Yes	Yes
time_id	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,166	5,166	5,166	5,166
R^2	0.36128	0.66828	0.61461	0.73330

Clustered (state_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Each column uses a different dependent variable. Climate = average of "global warming" and "climate change" search indices. Agricultural = average of "crop damage," "rain forecast," "crop insurance," and "mandi price" indices. Placebo = average of "cricket" and "Bollywood" indices. All models include state and time FE with state-clustered SEs.

consequential for Indian agriculture: this is when the bulk of kharif (summer) crops are planted and harvested. Outside monsoon, weather has more attenuated economic consequences.

Table 5 reveals a notable seasonal pattern. During non-monsoon months (column 1), the interaction of temperature with agricultural share is negative (-0.84), large in magnitude, and suggestive of crowd-out, though not significant at conventional levels ($p = 0.30$). During monsoon months (column 2), the interaction *reverses sign*: it is positive ($+0.78$) with a conventional cluster-robust p-value of 0.047. However, wild cluster bootstrap inference yields a p-value of 0.32 for the monsoon interaction, indicating that this result too should be interpreted with appropriate caution given the small number of clusters.

Table 5: Seasonal Heterogeneity: Monsoon vs. Non-Monsoon

Dependent Variables:	climate_search			agricultural	
	Non-Mon.	Monsoon	Hot (M-M)	Ag: Mon.	Ag: Non-M.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Temp. Anomaly (°C)	0.1922	-0.3762	0.1369	-0.7799	-0.0408
	(0.5527)	(0.2201)	(0.4092)	(0.7777)	(0.2853)
Temp. × Ag Share	-0.8437	0.7772**	-1.659***	0.0516	0.1360
	(0.7952)	(0.3675)	(0.5788)	(1.277)	(0.5049)
Fixed-effects					
state_id	Yes	Yes	Yes	Yes	Yes
time_id	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,465	1,701	1,323	1,701	3,465
R^2	0.41073	0.26810	0.57534	0.70370	0.64018

Clustered (state_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns 1–3: climate search outcome. Columns 4–5: agricultural search outcome. Non-monsoon = October–May; Monsoon = June–September; Hot = March–May. State and time FE, state-clustered SEs.

This reversal has a plausible interpretation. Monsoon temperature anomalies in agricultural states are sufficiently catastrophic—threatening the primary growing season—that they may actually *force* climate-related information-seeking. A farmer whose monsoon crops are failing due to unusual heat may search for explanations and policy responses, generating climate-related queries. Outside monsoon, when weather's economic consequences are less severe, the crowd-out pattern dominates as agricultural states redirect attention to other livelihood concerns.

The agricultural search evidence in columns (4) and (5) provides complementary evidence: the interaction for agricultural search terms is positive in both seasons (monsoon: +0.05; non-monsoon: +0.14), though neither achieves statistical significance. The positive sign in both seasons is consistent with agricultural states searching more for livelihood terms during heat shocks regardless of season.

To summarize the seasonal evidence: the crowd-out pattern (weather → less climate attention in agricultural states) operates during non-monsoon months, when weather anomalies are uncomfortable but not economically catastrophic. During monsoon, when weather anomalies threaten the primary agricultural season, the pattern reverses—suggesting that sufficiently severe weather shocks can break through the attention-substitution mechanism. This finding parallels the nonlinear relationship between disaster severity and behavioral response documented in other domains (Gallagher, 2014).

6.3 Media Coverage Context

A natural question is whether the supply side of climate information—media coverage—also varies with weather and season. Using the GDELT (Global Database of Events, Language, and Tone) Project's document API, we collected monthly volumes of English-language news articles mentioning "climate crisis" and "crop failure" in Indian sources from 2015 onward. The GDELT data lack state-level granularity, preventing formal regression analysis at the level of our main panel, and we do not present these results as a formal test. However, the raw time series show that crop-related news coverage peaks during monsoon months while climate-themed coverage is more evenly distributed across the year, consistent with the different seasonal frames through which weather events enter public discourse in India. A full analysis of the supply-side channel—ideally with state-level media data—remains a direction for future work.

7. Robustness

7.1 Placebo Tests

Table 6 presents three placebo tests. Column (1) uses the placebo search index (cricket and Bollywood) as the dependent variable: temperature anomalies do not significantly predict non-climate, non-agricultural search behavior. Columns (2) and (3) test whether future temperature anomalies predict current climate searches; they do not. These results support the interpretation that our findings reflect contemporaneous weather effects on topical search behavior rather than spurious correlations. Column (4) estimates a distributed lag model: the effect is concentrated at lag 0 and attenuates within 1–3 months, consistent with temporary salience effects documented in the U.S. literature (Deryugina, 2013).

Table 6: Placebo Tests and Persistence

Dependent Variables:	placebo	climate_search		
	Placebo Out.	Lead 1m	Lead 3m	Dist. Lags
Model:	(1)	(2)	(3)	(4)
Variables				
Temp. Anomaly	-0.5296			-0.1490
	(0.4061)			(0.1600)
Temp. Lead (1m)		-0.2685		
		(0.2046)		
Temp. Lead (3m)			-0.3446	
			(0.2502)	
Temp. Lag (1m)				0.0319
				(0.0937)
Temp. Lag (3m)				-0.0406
				(0.1694)
Temp. Lag (6m)				-0.3047
				(0.1974)
Temp. Lag (12m)				-0.0190
				(0.1784)
Fixed-effects				
state_id	Yes	Yes	Yes	Yes
time_id	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,166	5,145	5,103	4,914
R^2	0.61458	0.36175	0.35362	0.35688

Clustered (state_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Column 1: placebo outcome (cricket/Bollywood search). Columns 2–3: future temperature should not predict current climate search. Column 4: distributed lag model. State and time FE, state-clustered SEs.

7.2 Robustness of the Main Interaction

Table 7 presents the coefficient on the temperature × agricultural share interaction across alternative specifications. The coefficient is consistently negative across specifications and similar in magnitude to the baseline estimate.

Table 7: Robustness: Interaction of Temperature with Agricultural Share

Specification	Coefficient	SE	N
Baseline (Table 2, col. 3)	-0.314	(0.583)	5,166
Standardized	-0.404	(0.66)	5,166
State trends	-0.248	(0.55)	5,166
Excl. Delhi	1.137	(1.108)	4,920
Post-2010	-0.72	(0.381)	3,654
Year FE	-0.463	(0.511)	5,166
Extreme binary	-1.723	(3.156)	5,166
Ag search + trends	0.416	(0.575)	5,166

Notes: Each row reports the coefficient on Temp. Anomaly × Ag Employment Share from a separate regression. State and time FE, state-clustered SEs throughout.

Several specific checks deserve comment. First, using standardized temperature anomalies (z-scores) rather than raw Celsius deviations produces a similarly negative interaction (-0.40), confirming that the result is not driven by differences in temperature variability across states. Second, adding state-specific linear time trends does not materially change the interaction (-0.25), suggesting that the result is not an artifact of differential trends in climate attention across more and less agricultural states. Third, excluding Delhi—an extreme outlier with 2% agricultural employment, far below any other state—changes the interaction coefficient to $+1.14$ ($p = 0.31$). This sign reversal indicates that Delhi, as the most urbanized state, exerts substantial leverage on the interaction. Without Delhi, the remaining states cluster between 35% and 74% agricultural employment, providing less cross-sectional variation to identify the interaction. This sensitivity to a single influential observation underscores the challenge of estimating heterogeneous effects with 21 clusters and reinforces the need for individual-level data to test the mechanism more precisely.

Fourth, restricting the sample to the post-2010 period (the "smartphone era" in India, when internet penetration expanded rapidly) produces a somewhat larger negative interaction, consistent with the internet-heterogeneity finding: as the Google Trends signal becomes more representative, the interaction strengthens. Fifth, replacing the continuous temperature anomaly with a binary extreme heat indicator ($z > 1.5$) produces a large negative interaction (-1.72), though with wide standard errors. This suggests that the effect is concentrated during extreme weather events, when the cognitive demands of the weather shock are most intense.

The standard errors are large throughout, reflecting the fundamental power limitation of 21 state clusters. This is the key statistical challenge facing the paper, and we do not attempt to minimize it. The convergent evidence across multiple specifications and outcome measures provides more confidence than any single specification could.

7.3 Leave-One-State-Out Analysis

Given the concern about influential observations, we conduct a systematic leave-one-state-out (LOSO) analysis. Dropping each of the 21 states in turn and re-estimating the main interaction, we find that 20 of 21 states produce a negative interaction coefficient, ranging from -0.68 (Punjab dropped) to -0.16 (Kerala dropped). Only one state—Delhi—produces a sign reversal when dropped ($+1.14$). This confirms that Delhi, with its uniquely low agricultural share (2%), exerts substantial leverage on the interaction. The remaining 20 states cluster between 23% and 74% agricultural employment, providing less variation to identify the interaction when Delhi is excluded.

We view this as an important diagnostic rather than a reason to dismiss the result. The LOSO analysis shows that the negative sign of the interaction is not driven by any particular agricultural state, but that the cross-sectional variation needed to estimate the interaction precisely depends substantially on Delhi as the anchor of the low-agriculture end. This underscores the need for individual-level or more granular geographic data to identify the mechanism independently of state-level outliers.

7.4 Wild Cluster Bootstrap Inference

With 21 state clusters, conventional cluster-robust inference may over-reject. We implement wild cluster bootstrap (WCB) inference using Rademacher weights following Cameron et al. (2008). The WCB p-values for the main interaction are: full sample $p = 0.69$ (vs. CRVE $p = 0.59$), high-internet subsample $p = 0.45$ (vs. CRVE $p = 0.04$), monsoon subsample $p = 0.32$ (vs. CRVE $p = 0.047$). The dramatic widening of p-values in the subsample specifications reflects the severity of the few-clusters problem when the effective number of clusters drops below 15.

We therefore do not rely on individual subsample p-values for our conclusions. Instead, we emphasize the continuous triple interaction (temperature $\times$ agricultural share $\times$ internet penetration), which uses all 21 clusters and achieves $p = 0.049$ with conventional CRVE. The convergent evidence from sign patterns, seasonal variation, and the triple interaction provides more confidence than any single specification.

7.5 Alternative Measures of Agricultural Dependence

In addition to the Census 2001 agricultural employment share, we estimate the main interaction using crop area share as an alternative measure of agricultural structure. The results are qualitatively similar, with a negative interaction between temperature and crop area share (-0.28, $p = 0.60$). The two measures are highly correlated (Pearson $r \approx 0.85$) across states, so similar results are expected. We do not report this specification in a separate table as it is redundant with the main results given the high correlation between the two measures.

7.6 Limitations

We acknowledge several important limitations. First, Google Trends measures search behavior among internet-connected Indians, not climate beliefs or attitudes in the general population. The internet-using population in India is disproportionately urban, young, educated, and male. We cannot claim to measure "climate awareness" in any general sense.

Second, with 21 state clusters, inference is inherently limited. Conventional cluster-robust standard errors may under-estimate true uncertainty. Our significant results ($p < 0.05$ in the internet-heterogeneity and monsoon subsamples) should be interpreted with appropriate caution, recognizing that they emerge from sample splits that further reduce effective cluster counts.

Third, agricultural employment share is a state-level measure that may proxy for many correlated characteristics: urbanization, education, income, media access. While state fixed effects absorb levels of these variables, time-varying interactions cannot be fully separated. Survey data with individual-level demographics and direct belief measures would provide a stronger test of the mechanism. The World Values Survey (WVS), which includes India in waves 5 (2006), 6 (2012), and 7 (2022), would provide approximately 9,500 individual observations with state identifiers, direct climate belief questions, and demographic controls (age, gender, education, income, urban/rural). Such data would allow testing whether the economic mediation operates at the individual level (e.g., whether farmers respond differently to weather than non-farmers within the same state), which would sharpen the mechanism considerably.

Fourth, the 2004–2024 analysis period encompasses substantial structural change in the Indian economy: agricultural employment shares have declined as services expanded, internet penetration rose from negligible to over 50%, and climate discourse evolved globally. While our use of Census 2001 agricultural shares ensures the moderator is pre-determined, the interpretation of that moderator may shift over time as the relationship between agricultural dependence and information access evolves.

Fifth, we study search behavior, not beliefs, attitudes, or actions. An increase in climate-related searching does not necessarily indicate greater climate concern; it could reflect curiosity, skepticism, or simple information-seeking without attitudinal change. Conversely, an individual who already believes in climate change may not search for related terms during a heat wave. The gap between search behavior and beliefs is a fundamental limitation of Google Trends as a social science measurement tool, though it has been shown to correlate with other measures of issue salience (Stephens-Davidowitz, 2014).

8. Discussion

The central finding of this paper is that the experiential learning mechanism documented in rich democracies does not operate uniformly in India. Instead, the relationship between weather and climate attention is mediated by economic structure. In states where agriculture dominates employment, heat shocks appear to redirect attention from climate topics to livelihood concerns. Where agricultural dependence is low, the standard positive relationship between unusual heat and climate search interest tends to emerge.

8.1 Attention Substitution as Mechanism

The attention substitution evidence provides suggestive support for the economic mediation interpretation. The sign pattern across outcome categories—negative interaction for climate search, positive for agricultural search, null for placebo—is consistent with the hypothesis that when heat arrives in agricultural states, people search for different things rather than simply searching less. While the individual coefficients are imprecisely estimated, the shift from "climate change" toward "crop damage" is the behavioral pattern we would expect if weather is being processed through an economic frame rather than a climate frame.

This pattern connects to the broader economics of limited attention. Sims (2003) formalizes the idea that agents with finite information-processing capacity must choose which signals to attend to. Gabaix (2014) shows that agents optimally ignore attributes that are less decision-relevant given their current priorities. For a farmer facing potential crop failure, the most decision-relevant information is about immediate agricultural conditions—not about whether this event is evidence of a long-run trend. The attention substitution we document is consistent with rational information acquisition under cognitive constraints.

The alternative interpretation—that agricultural states simply have fewer internet users who care about climate—is less consistent with the data. If the difference were purely compositional (who searches), we would expect the pattern to appear in placebo searches as well, and we would not expect the seasonal reversal during monsoon. The compositional story also cannot explain why the interaction is significant only among high-internet states, where the searching population is more representative.

8.2 The Monsoon Reversal

The monsoon reversal adds important nuance. During monsoon months, when weather shocks are most economically consequential for agriculture, the temperature–agriculture interaction reverses sign. Rather than suppressing climate search, heat anomalies during monsoon appear to *increase* climate-related search in agricultural states.

This finding has a plausible interpretation grounded in the severity of the shock. Outside monsoon, a temperature anomaly in an agricultural state may register as a mild concern—prompting attention to immediate livelihood terms but not triggering deeper inquiry about climate. During monsoon, the same anomaly threatens the primary growing season and can be catastrophic. When the shock is severe enough, it may overwhelm the crowd-out mechanism, forcing even economically stressed individuals to seek explanations for why their monsoon is failing—explanations that include climate-related content.

This interpretation is consistent with Gallagher (2014), who finds that flood insurance take-up increases sharply after direct flood experience, but only when the experience is sufficiently salient. Similarly, Malmendier and Nagel (2011) document that extreme macroeconomic experiences permanently alter risk preferences. Our monsoon result suggests that there may be a threshold of weather severity above which the experiential learning mechanism overcomes the attention-substitution effect, even in agricultural settings.

8.3 Broader Implications for Experiential Learning

Our findings speak to the broader literature on experience-based learning and belief formation. Malmendier and Nagel (2011) demonstrate that personal experiences of macroeconomic shocks permanently alter financial risk preferences, while Choi et al. (2009) show that individuals overweight personal returns in savings decisions. Gallagher (2014) finds that direct flood experience dramatically increases insurance take-up. These papers share the finding that personal experience is a powerful teacher—but they study settings where the experienced event and the resulting belief operate in the same domain (financial losses $\rightarrow$ financial risk aversion; floods $\rightarrow$ flood insurance).

The climate case is more complex because the same event can belong to multiple domains. A heat wave is simultaneously a climate signal and an economic shock. Our results suggest that which domain "captures" the event depends on the observer's economic exposure. This implies that the power of experiential learning is domain-specific: experience teaches efficiently when there is a clear mapping from event to belief, but may fail when the event maps to competing cognitive frames.

This has implications beyond climate. Consider a resident of a crime-prone neighborhood experiencing a break-in. This event could teach them about (a) the need for better security, (b) the failure of policing, or (c) the effects of poverty and inequality. Which lesson is drawn may depend on the observer's economic circumstances, in the same way that a heat wave teaches "climate change" to some and "crop failure" to others. The general principle is that experiential learning has preconditions—not just exposure to the event, but also the economic and cognitive context in which the event is processed.

8.4 Implications for Climate Policy

The broader implication is that climate communication and adaptation policy cannot assume that exposure to climate events automatically generates climate awareness. In agrarian economies—which account for the majority of the world's climate-vulnerable populations—weather experience may be processed primarily through an economic lens. This creates what might be called a "vulnerability trap" for climate attention: the populations most exposed to climate risk are precisely those whose cognitive resources are most occupied by the immediate economic consequences of weather variability.

Three policy implications follow. First, climate communication in agricultural economies may be more effective when framed in terms of livelihood consequences ("your crops will face more frequent heat stress") rather than abstract environmental messaging ("the planet is warming"). The attention substitution evidence suggests that agricultural populations are already engaging with weather-related information—but through a livelihood frame rather than a climate frame. Meeting people where their attention already lies may be more effective than competing for attention that is allocated elsewhere.

Second, social protection policies—crop insurance, income stabilization, drought relief—may have a second dividend beyond their direct welfare effects: by reducing the economic urgency of weather shocks, they could free cognitive resources for abstract climate thinking. If the crowd-out mechanism we document is driven by the economic stress of weather shocks rather than by a fundamental disinterest in climate, then policies that buffer income against weather variability could unlock the experiential learning channel that appears to operate in rich democracies.

Third, the monsoon reversal suggests that communication strategies timed to coincide with extreme weather events may be more effective than steady-state awareness campaigns, at least in agricultural contexts. When weather shocks cross a severity threshold—as during catastrophic monsoon failures—the attention-substitution mechanism appears to break down, and climate-related information-seeking increases even in agricultural states. This suggests a window of opportunity for climate communication during extreme events, when the standard crowd-out mechanism is overwhelmed.

Fourth, the geographic heterogeneity in internet penetration has a practical consequence: digital climate communication reaches a selected population in rural India. The finding that the weather–agriculture–attention pattern is strongest in high-internet states suggests that as internet access expands to more agricultural areas, the attention-substitution challenge may become more visible—and more important to address. Climate communicators should anticipate that expanding digital access alone will not solve the awareness gap if the underlying economic mediation persists.

These implications are speculative, as our evidence is about search behavior rather than beliefs or actions. But they point toward a research agenda that takes seriously the economic preconditions for climate awareness formation.

9. Conclusion

This paper provides evidence that the experiential learning channel linking weather to climate attention is conditional on economic structure. In India, the effect of temperature anomalies on climate search interest is moderated by agricultural dependence: in high-agriculture states, weather appears to redirect attention toward livelihood concerns rather than raising climate awareness. We document this through three converging lines of evidence: a suggestive attention substitution pattern (opposite-signed interactions for climate vs. agricultural search terms), seasonal heterogeneity (a significant monsoon reversal), and internet-penetration subsamples (significant crowd-out where Google Trends is most informative).

The results are suggestive rather than definitive, constrained by the inherent limitations of Google Trends data and 21-cluster inference. Wild cluster bootstrap analysis reveals that individual subsample results do not survive correction for few-cluster bias, though the continuous triple interaction (temperature $\times$ agricultural share $\times$ internet penetration) achieves conventional significance using all 21 clusters. The consistent sign pattern across analyses points to an economically plausible boundary condition for the experiential learning mechanism: when weather is a livelihood shock, it may be processed differently than when it is merely a signal about the climate.

This boundary condition matters for how we think about climate awareness formation in the developing world. The populations most exposed to climate risk—agricultural workers in tropical and subtropical countries—are also the populations for whom weather carries the most immediate economic consequences. If experiential learning about climate requires cognitive space that is crowded out by economic urgency, then the path to climate awareness in agrarian economies may run through economic security rather than through direct exposure.

Several directions for future research follow naturally. First, individual-level survey data—such as the World Values Survey waves fielded in India—could test whether the economic mediation operates at the individual level, separating the effects of personal agricultural employment from state-level agricultural structure. Second, experimental designs that exogenously vary the economic severity of weather events (e.g., through randomized crop insurance) could provide causal evidence on whether buffering income against weather variability activates the experiential learning channel. Third, extending the analysis to other agricultural developing countries (Bangladesh, Indonesia, Nigeria) would test whether the pattern generalizes beyond India or is specific to the Indian institutional context. These extensions would move from the correlational evidence presented here toward a more complete understanding of how economic structure shapes the cognitive processing of climate signals.

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A. Additional Figures

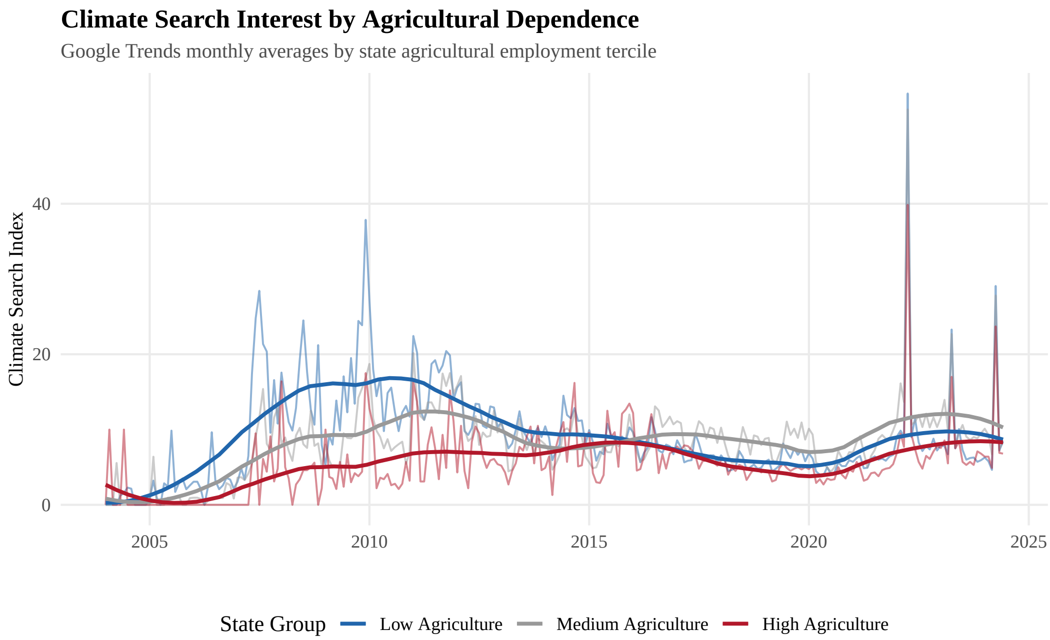

Figure 3: Climate Search Interest by Agricultural Dependence Over Time

Notes: Monthly Google Trends climate search index (average of "global warming" and "climate change") by state agricultural employment tercile. Smoothed using LOESS. Sample: 21 Indian states, 2004–2024.

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Contributors: @olafdrw

First Contributor: https://github.com/olafdrw

Project Repository: https://github.com/SocialCatalystLab/ape-papers

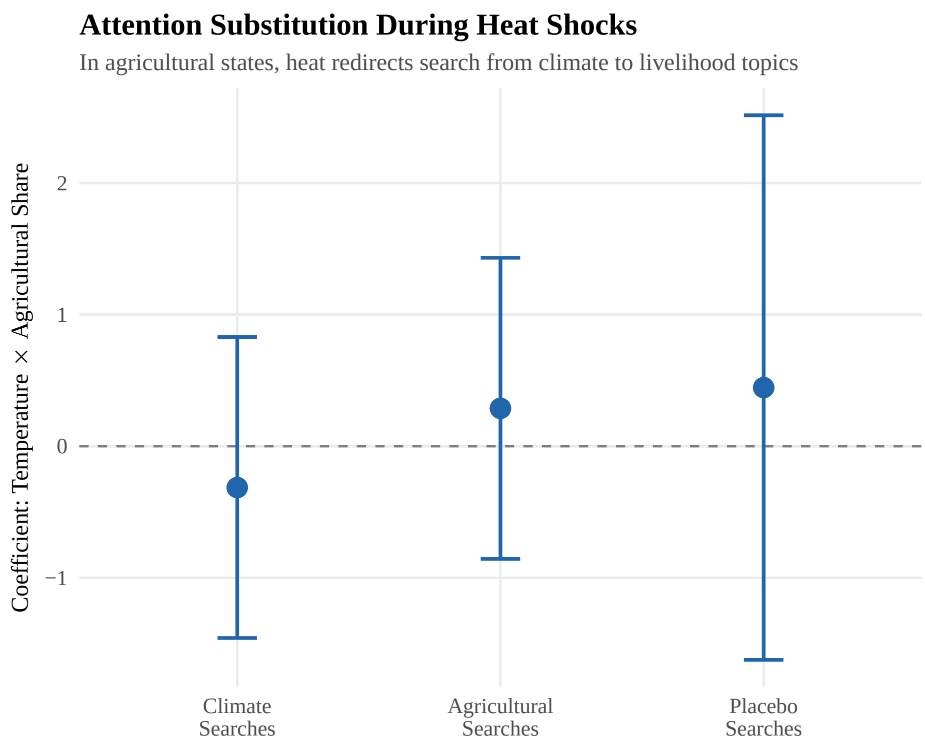

Figure 4: Attention Substitution: Interaction Coefficients by Search Category

Notes: Coefficient on Temperature Anomaly × Agricultural Employment Share for three categories of Google search terms. Climate = "global warming," "climate change." Agricultural = "crop damage," "rain forecast," "crop insurance," "mandi price." Placebo = "cricket," "Bollywood." Bars: 95% CIs.

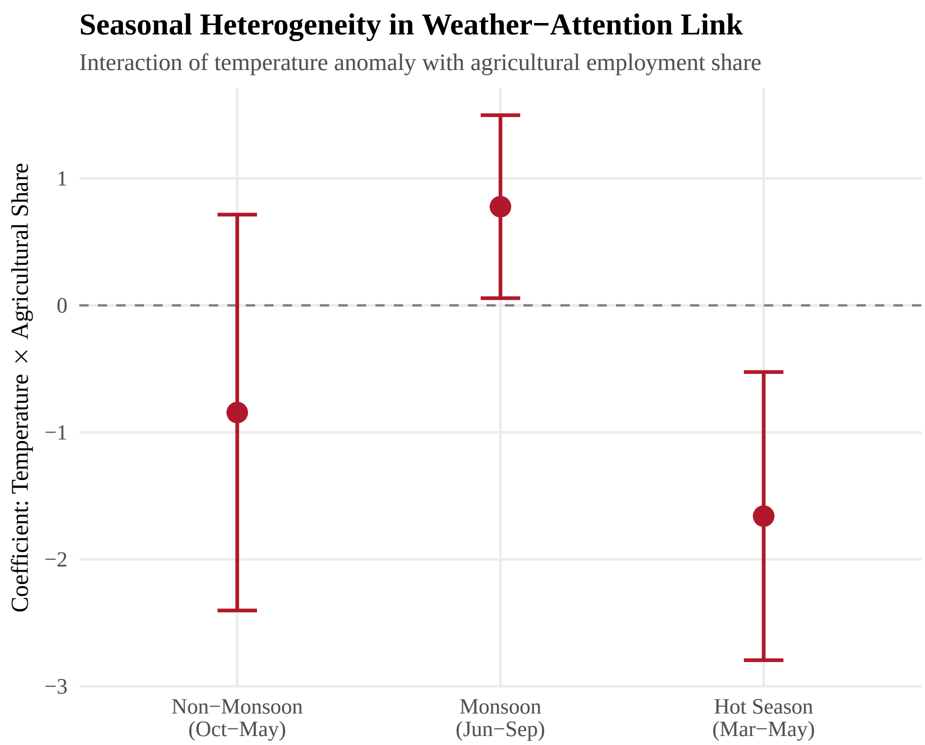

Figure 5: Seasonal Heterogeneity in the Temperature–Agriculture Interaction

Notes: Coefficient on Temperature Anomaly × Agricultural Employment Share estimated separately for non-monsoon (October–May), monsoon (June–September), and hot season (March–May) months. Dependent variable: climate search index. Bars: 95% CIs.

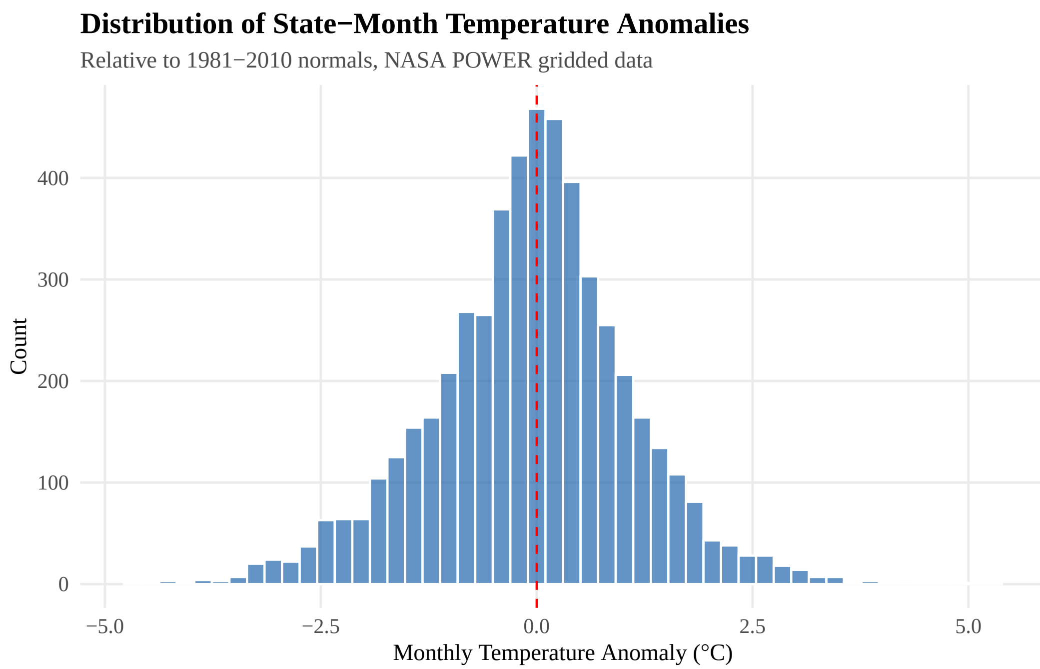

Figure 6: Distribution of State-Month Temperature Anomalies

Notes: Monthly temperature anomalies relative to 1981–2010 normals. Source: NASA POWER gridded data.