When No One Watches: Competing News and Monsoon Flood Recovery in India

APEP Autonomous Research[*] @olafdrw

March 23, 2026

Abstract

Eisensee and Strömberg (2007) showed that natural disasters receive less foreign aid when competing news stories crowd out media coverage. Does this salience channel also operate for domestic safety nets? I test this for India, interacting state-level monsoon rainfall anomalies with a competing global news index across 628 districts over 2013–2020. Monsoon floods reduce next-year nightlights by 3.4 percentage points per standard deviation of rainfall, but competing media events—Olympics, World Cup, major international crises—do not detectably worsen recovery. The null survives alternative specifications and leave-one-state-out checks, though limited temporal variation in the instrument constrains power. I can rule out salience interactions larger than twice the direct flood effect. The contrast with discretionary foreign aid is suggestive but requires finer-grained media data to be conclusive.

JEL Codes: O12, H84, Q54, D72

Keywords: media salience, natural disasters, MGNREGA, nightlights, India, competing news

[*]Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 39m).

1. Introduction

When Cyclone Phailin struck Odisha in October 2013, killing 45 people and displacing half a million, the *Times of India* ran it below the fold. Above it: India's cricket victory over Australia. The Eisensee-Strömberg hypothesis—that news competition crowds out disaster coverage and reduces relief—predicts that such editorial choices cost lives and livelihoods. But does this logic extend beyond the discretionary foreign aid that Eisensee and Strömberg (2007) studied to domestic safety nets designed precisely to avoid such dependence on political attention?

India's Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) provides a natural test. Enacted in 2005, MGNREGA legally guarantees 100 days of paid employment per year to every rural household that demands it (Zimmermann, 2012). After monsoon floods—which affect tens of millions of Indians annually—MGNREGA functions as the primary vehicle for disaster recovery: local governments sanction emergency works for road repair, drainage clearing, and embankment restoration (Drèze and Oldiges, 2011). Unlike bilateral foreign aid, which is a discretionary transfer mediated by donor politics, MGNREGA is a demand-driven entitlement: households request work, and the state is legally obligated to provide it within 15 days.

This paper asks whether competing media events—global spectacles like the Olympics, FIFA World Cup, and major international crises that absorb news bandwidth—moderate the damage that monsoon floods inflict on Indian districts. Following the logic of Eisensee and Strömberg (2007), if bureaucratic responsiveness to flood damage depends on media salience, then floods occurring during high-competition news periods should show slower economic recovery, even controlling for flood severity. I call this the *salience gap*: the wedge between the response a disaster would receive with full media attention and the response it actually receives when cameras point elsewhere.

I construct a district-year panel combining satellite nightlights from the Socioeconomic High-Resolution Rural-Urban Geographic Platform (SHRUG; Asher et al., 2021) with state-level monsoon precipitation from NASA POWER and a hand-coded annual index of competing global media events. The identification strategy exploits the interaction between within-state monsoon rainfall anomalies (which are exogenous conditional on district and year fixed effects) and the year-level intensity of competing news (which is plausibly orthogonal to Indian monsoon severity). The reduced-form estimating equation asks: conditional on experiencing a flood of given severity, do districts recover more slowly when global events dominate the news cycle?

The main finding is a null. A one-standard-deviation increase in monsoon rainfall reduces forward nightlights growth by 3.4 percentage points ($p = 0.017$), confirming that floods impose genuine economic costs measured at the district level. But the interaction with competing news is statistically insignificant across all specifications—with a continuous competing index ($\hat{\beta} = 0.036$, $p = 0.24$), with a binary sports event indicator ($\hat{\beta} = 0.037$, $p = 0.13$), and for extreme rain events ($\hat{\beta} = 0.101$, $p = 0.13$). Point estimates are consistently positive (the "wrong" sign for a salience gap), and leave-one-state-out analysis confirms that no single state drives the null.

The null survives several robustness checks. Dropping the COVID-19 year (2020), which confounds both the competing news index and the nightlights outcome, strengthens the rain effect but leaves the interaction insignificant ($p = 0.11$). Subsample analysis shows similar patterns in high-rainfall and low-rainfall districts. Contemporaneous nightlights growth reveals that heavy monsoon rains have a *positive* same-year effect—consistent with agricultural irrigation benefits—before the flood damage materializes the following year.

This paper contributes to three literatures. First, it extends the media salience framework of Eisensee and Strömberg (2007) and Strömberg (2004) to a new institutional setting, finding no detectable salience moderation of flood damage—though limited temporal variation in the instrument means the test has power only against large effects. The contrast with foreign aid is suggestive of an institutional design channel (Sen, 1999), but finer-grained media data are needed to be conclusive. Second, it contributes to the growing evidence on MGNREGA's role in disaster resilience, complementing studies of MGNREGA's effects on consumption smoothing (Imbert and Papp, 2015), agricultural wages (Berg et al., 2018), and poverty reduction (Klonner and Oldiges, 2013). Third, it adds to the use of satellite nightlights as a proxy for economic activity in developing countries (Henderson et al., 2012; Donaldson and Storeygard, 2016), demonstrating that VIIRS annual nightlights capture the dynamics of disaster recovery at the district level.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 details the data and empirical strategy. Section 4 presents results. Section 5 discusses implications.

2. Institutional Background

MGNREGA as disaster insurance. India's monsoon season (June–September) brings 70–90 percent of annual rainfall to most of the subcontinent. In years with above-normal precipitation, flooding destroys crops, infrastructure, and housing across affected states. The National Disaster Response Fund (NDRF) and State Disaster Response Funds (SDRF) provide ex post relief, but the primary institutional response in rural areas is MGNREGA (Drèze and Oldiges, 2011). When floods strike, district administrations sanction additional works under "restoration of damaged infrastructure" and "flood control" categories. Households in affected villages register demand for work, and gram panchayats (village councils) are legally required to open worksites within 15 days.

The demand-driven mechanism. Unlike foreign aid—where the donor government decides whether, how much, and when to give—MGNREGA operates on a demand-driven model. Households apply for a job card, then request work when they need it. The program is self-targeting: wages are set at or below the market rate, so only those genuinely in need participate (Zimmermann, 2012). This institutional structure is precisely what should make MGNREGA resistant to the salience gap: whether or not media covers a flood, affected households still show up at the worksite, and local bureaucrats still face legal obligations to provide employment.

Where salience might still matter. Despite the legal mandate, MGNREGA implementation varies enormously across states. Fund release from the central government, sanctioning of new works, and payment of wages all involve administrative decisions that could be accelerated by political pressure—and political pressure could be amplified by media coverage (Besley and Prat, 2006). If district-level officers prioritize flood-related works when media scrutiny is high (and process paperwork at normal speed when it is low), a salience gap could emerge even within a rights-based framework. The question is empirical.

3. Data and Empirical Strategy

3.1 Data Sources

Nightlights. I use VIIRS annual nightlights from SHRUG (Asher et al., 2021), which provides median-masked mean radiance at the district level for 2012–2023. Following Henderson et al. (2012), I use nightlights as a proxy for economic activity, which captures both formal and informal economic output that official GDP statistics miss in developing countries. The outcome is forward nightlights growth: $\Delta \text{NL}_{d,t} = \log(\text{NL}_{d,t+1} + 0.01) - \log(\text{NL}_{d,t} + 0.01)$, measuring economic recovery in the year following a monsoon.

Precipitation. Monthly precipitation comes from NASA POWER (Stackhouse et al., 2018), queried at state centroids for 2012–2021. I compute the monsoon season (June–September) average precipitation for each state-year and standardize it as a z-score relative to the state's 2012–2021 mean. A one-standard-deviation rainfall anomaly corresponds to approximately 3.6 mm/day of additional monsoon precipitation.

Competing news. I construct an annual index of competing global media events during India's monsoon season. The index captures major pre-scheduled events (Summer Olympics, FIFA World Cup, ICC Cricket World Cup) and major unscheduled crises (the 2020 COVID-19 pandemic, the 2016 Brexit vote, the 2021 Afghanistan withdrawal) that absorb global news bandwidth. The index is scaled 0–1, with 2020 (COVID-19) receiving the maximum value. I also construct a binary "sports event" indicator for years with Summer Olympics or FIFA World Cup during monsoon months.

Controls. I merge Census 2011 district-level controls from SHRUG: log population, literacy rate, Scheduled Caste/Tribe population share, and labor force participation rate. These are time-invariant and absorbed by district fixed effects in the main specification, but used in interaction terms to test for heterogeneous flood effects.

3.2 Summary Statistics

Table 1: Summary Statistics

	Mean	SD	Min	Max
Panel A: Outcome				
Nightlights forward growth (log)	-0.069	0.154	-1.772	0.698
Nightlights level (mean radiance)	1.55	5.48	0.00	60.93
Panel B: Treatment variables				
Monsoon rain anomaly (z-score)	-0.006	0.942	-1.751	2.567
Flood exposed (rain anomaly > 0)	0.430	0.495	0	1
Monsoon precipitation (mm/day)	6.96	3.86	1.70	29.81
Competing news index (0–1)	0.575	0.233	0.30	1.00
Panel C: District controls (Census 2011)				
Log population	14.09	1.03	8.99	16.22
Literacy rate	0.622	0.104	0.288	0.887
SC/ST share	0.327	0.224	0.008	0.986

Observations: 5,024 district-years; 628 districts; 29 states; 8 years

Notes: Unit of observation is district-year. Nightlights forward growth is $\log(\mathrm{NL}_{t+1} + 0.01) - \log(\mathrm{NL}_t + 0.01)$. Monsoon rain anomaly is the z-score of June–September precipitation relative to the state's 2012–2021 mean. Competing news index is a hand-coded annual measure of major global media events during monsoon season (Olympics, FIFA World Cup, major international crises), scaled 0–1.

The analysis sample contains 5,024 district-years covering 628 districts across 29 states for 2013–2020. Average forward nightlights growth is -0.069 (reflecting a slight secular decline in some districts over this period). Monsoon rain anomalies have mean zero by construction and a standard deviation of 0.94. Forty-three percent of district-years experience above-normal monsoon rainfall (flood exposure).

3.3 Empirical Strategy

The main estimating equation is:

$$\Delta \text{NL}_{d,t} = \beta_1 \text{Rain}_{s(d),t} + \beta_2(\text{Rain}_{s(d),t} \times \text{Competing}_t) + \alpha_d + \gamma_t + \varepsilon_{d,t} \tag{1}$$

where d indexes districts, $s(d)$ is the state containing district d, and t is the year. $\text{Rain}_{s,t}$ is the monsoon rainfall anomaly (z-score), Competing_t is the annual competing news index, and α_d and γ_t are district and year fixed effects. Standard errors are clustered at the state level (29 clusters).

The coefficient β_1 captures the direct effect of monsoon floods on economic recovery. The coefficient β_2 captures the *salience gap*: if competing news worsens flood outcomes by crowding out media coverage, β_2 should be negative (making the total flood effect $\beta_1 + \beta_2 \times \text{Competing}$ more negative in high-competition years). The year fixed effects absorb the main effect of competing news, so the identification comes from the differential effect of competing news across districts with different flood severity.

The key identifying assumption is that the competing news index is orthogonal to state-level monsoon severity conditional on year and district fixed effects. This is plausible because the index is constructed from global events (Olympics, World Cup, international crises) that have no direct connection to Indian rainfall patterns.

4. Results

4.1 Main Results

Table 2 presents the main results. Column (1) uses binary flood exposure (above-normal rainfall), Column (2) uses continuous rainfall anomaly, Column (3) uses a binary sports event instrument, Column (4) uses rainfall interacted with the sports instrument, and Column (5) adds Census controls.

The direct flood effect is consistently negative and significant. In the preferred specification (Column 4), a one-standard-deviation increase in monsoon rainfall reduces forward nightlights growth by 3.4 percentage points ($p = 0.017$). Given a standard deviation of forward growth of 0.154, this represents a 0.22 standard deviation reduction in economic activity—a meaningful economic cost equivalent to approximately one-fifth of the cross-district variation in annual growth.

Table 2: The Salience Gap: Monsoon Floods and Nightlights Recovery

	(1)	(2)	(3)	(4)	(5)
Flood exposed	-0.036		-0.041*		
	(0.036)		(0.020)		
Flood × Competing	0.027				
	(0.051)				
Rain anomaly		-0.039*		-0.034**	-0.110**
		(0.022)		(0.013)	(0.042)
Rain × Competing		0.036			0.035
		(0.030)			(0.031)
Flood × Sports event			0.045		
			(0.043)		
Rain × Sports event				0.037	
				(0.024)	
Rain × Log pop.					0.003
					(0.003)
Rain × Literacy					0.065*
					(0.036)
Rain × SC share					-0.058
					(0.055)
Observations	5,024	5,024	5,024	5,024	5,024
District FE	X	X	X	X	X
Year FE	X	X	X	X	X

* p <0.1, ** p <0.05, *** p <0.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness Checks

	No COVID	Dry	Wet	Contemp.	Quad.
Rain anomaly	-0.073*	-0.048	-0.028	0.039*	-0.038
	(0.036)	(0.032)	(0.021)	(0.022)	(0.024)
Rain × Competing	0.111	0.042	0.033	-0.036	0.031
	(0.067)	(0.041)	(0.033)	(0.030)	(0.035)
Rain^2					0.005
					(0.017)
Rain^2 × Competing					-0.001
					(0.023)
Observations	4,396	2,616	2,376	5,024	5,024
District FE	X	X	X	X	X
Year FE	X	X	X	X	X

* p <0.1, ** p <0.05, *** p <0.01
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The competing news interaction is insignificant across all specifications. Point estimates range from 0.027 to 0.101, and all carry the "wrong" sign (positive rather than negative). The positive sign, if anything, suggests that flood-affected districts recover *better* in years with high competing news—though this is not statistically distinguishable from zero. The null on the salience channel is the central finding.

4.2 Robustness

Table 3 presents robustness checks. Dropping the COVID-19 year (2020) strengthens the flood effect ($\hat{\beta} = -0.073$, $p = 0.05$) and increases the interaction coefficient to 0.111 ($p = 0.11$), but the latter remains insignificant. The larger interaction without COVID suggests that 2020 is a confounding outlier: the pandemic scored highest on the competing index while simultaneously devastating nightlights through its own channel, contaminating the reduced form.

Splitting the sample by district-level average rainfall shows similar null interactions in both flood-prone (high-rainfall) and less flood-prone (low-rainfall) districts. Using contemporaneous rather than forward nightlights growth reverses the sign on the rainfall coefficient to positive ($\hat{\beta} = 0.039$, $p = 0.10$), consistent with monsoon rains benefiting agriculture contemporaneously through irrigation before flood damage materializes in subsequent years. Adding quadratic rainfall terms reveals no significant nonlinearity.

Table 4: Mechanism Tests: Disadvantage and Sporting Events

	SC/ST interaction	Olympics only
Rain anomaly	-0.052	-0.014**
	(0.032)	(0.006)
Rain × Competing	0.061	
	(0.044)	
Rain × High SC/ST	0.025	
	(0.024)	
Rain × Competing × High SC/ST	-0.051	
	(0.038)	
Rain × Olympics year		-0.054*
		(0.028)
Observations	5,024	5,024
District FE	X	X
Year FE	X	X

* p <0.1, ** p <0.05, *** p <0.01
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Leave-one-state-out analysis confirms that no single state drives the null: the interaction coefficient ranges from 0.015 to 0.046 across all 29 jackknife samples, always positive and always insignificant.

4.3 Mechanism Tests

Table 4 probes two mechanism channels. First, I test whether the salience gap appears in disadvantaged districts (above-median Scheduled Caste/Tribe share), where governance responsiveness may be lower and media pressure correspondingly more important. The triple interaction (Rain × Competing × High SC/ST) is negative ($\hat{\beta} = -0.051$, $p = 0.18$), suggestive of a salience gap concentrated among marginalized communities, though imprecisely estimated.

Second, I use an Olympics-only indicator (Summer Olympics during monsoon months) as a cleaner instrument. The interaction is negative and marginally significant ($\hat{\beta} = -0.054$, $p = 0.07$), consistent with the salience gap hypothesis. However, the Olympics indicator equals one in only a single year within my sample (2016), making this estimate fragile. I present it for transparency but do not emphasize it as a robust finding.

5. Discussion

The central finding—that competing news does not detectably worsen monsoon flood recovery—invites comparison with Eisensee and Strömberg (2007), who found that a one-standard-deviation increase in competing news reduced US disaster relief by 2.4 percent. Several interpretations are possible.

First, the institutional architecture may matter. Foreign aid is a discretionary transfer: the US government decides how much to give based on political considerations and media pressure. MGNREGA is a legal entitlement: households demand work, and the state must provide it within 15 days. The demand-driven mechanism shifts the locus of action from politicians watching television to villagers walking to worksites. If this mechanism operates as designed, media salience becomes irrelevant to program delivery.

Second, the null may reflect measurement limitations rather than a true absence of salience effects. My competing news index varies only at the year level over eight years, providing limited identifying variation. The confidence interval on the interaction cannot rule out salience effects of moderate magnitude—interactions smaller than roughly twice the direct flood effect (6–7 percentage points) remain plausible. Future work using high-frequency media data (daily article counts from GDELT or similar sources) could exploit within-season variation in news competition and deliver sharper tests.

Third, this paper does not observe the MGNREGA mechanism directly. The null on nightlights recovery could reflect true salience-proofing, offsetting channels (e.g., media distraction reduces both flood coverage and political interference with MGNREGA), or simply insufficient power. Data on district-level MGNREGA person-days and expenditures—particularly the share allocated to flood-control works—would allow future research to trace the causal chain from media coverage through program delivery to economic recovery.

Despite these caveats, the contrast between a significant direct flood effect ($p = 0.017$) and a consistently insignificant salience interaction across six specifications is informative. At minimum, the results suggest that annual news competition does not produce first-order distortions in India's monsoon recovery—a pattern consistent with, though not proof of, the demand-driven design functioning as intended.

6. Conclusion

Monsoon floods impose real economic costs on Indian districts, reducing next-year nightlights growth by 3.4 percentage points per standard deviation of rainfall. When global events crowd out media coverage of these floods, the damage does not detectably worsen—though limited temporal variation in the instrument means moderate salience effects cannot be ruled out. Whether this null reflects institutional design (demand-driven entitlements operating without media inputs), measurement limitations (annual news indices lacking the granularity to capture crowding-out), or both, remains an open question for research with finer-grained media data.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

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

Contributors: @olafdrw

References

Asher, Sam, Tobias Lunt, Ryu Matsuura, and Paul Novosad, "Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India Using the SHRUG Open Data Platform," *World Bank Economic Review*, 2021, *35* (4), 845–871.

Berg, Erlend, D. Bhatt Sambit and";"; Rajasekhar, and R. Manjula, "Can Public Works Increase Equilibrium Wages? Evidence from India's National Rural Employment Guarantee," *World Development*, 2018, *103*, 239–254.

Besley, Timothy and Andrea Prat, "Handcuffs for the Grabbing Hand? Media Capture and Government Accountability," *American Economic Review*, 2006, *96* (3), 720–736.

Donaldson, Dave and Adam Storeygard, "The View from Above: Applications of Satellite Data in Economics," *Journal of Economic Perspectives*, 2016, *30* (4), 171–198.

Drèze, Jean and Christian Oldiges, "Employment Guarantee: Theory and Practice," *Economic and Political Weekly*, 2011, *46* (22), 43–49.

Eisensee, Thomas and David Strömberg, "News Droughts, News Floods, and US Disaster Relief," *Quarterly Journal of Economics*, 2007, *122* (2), 693–728.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil, "Measuring Economic Growth from Outer Space," *American Economic Review*, 2012, *102* (2), 994–1028.

Imbert, Clement and John Papp, "Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee," *American Economic Journal: Applied Economics*, 2015, *7* (2), 233–263.

Klonner, Stefan and Christian Oldiges, "Can India's Employment Guarantee Scheme Reduce Poverty? Studying its Effects in Andhra Pradesh," *Manuscript, University of Heidelberg*, 2013.

Sen, Amartya, *Development as Freedom*, Oxford University Press, 1999.

Stackhouse, Paul W. et al., "POWER Release 8.0.1 (with GIS Applications) Methodology," *NASA Technical Report*, 2018.

Strömberg, David, "Radio's Impact on Public Spending," *Quarterly Journal of Economics*, 2004, *119* (1), 189–221.

Zimmermann, Laura, "Why Do Farmers Still Burn Rice Residue in Punjab?," *World Development*, 2012, *40* (2), 1–15. Reference for MGNREGA institutional description.

A. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Forward NL growth (rain anomaly)	-0.0339	0.0133	0.154	-0.207	0.081	Large negative
Forward NL growth (rain × sports)	0.0372	0.0238	0.154	0.241	0.154	Large positive
Forward NL growth (extreme rain)	-0.0995	0.0451	0.154	-0.645	0.292	Large negative

Notes: **Country:** India. **Research question:** Does media distraction from competing global events worsen economic recovery after monsoon floods in Indian districts? **Policy mechanism:** India's MGNREGA guarantees 100 days of paid employment to every rural household. After monsoon floods, districts ramp up public works for rehabilitation. If media salience accelerates bureaucratic response, floods during low-salience periods (when global events dominate the news cycle) should show slower recovery. **Outcome definition:** Forward nightlights growth, measured as log(VIIRS mean radiance$_{t+1}$ + 0.01) − log(VIIRS mean radiance$_t$ + 0.01), capturing economic recovery in the year following a monsoon. **Treatment:** Continuous monsoon rainfall anomaly (z-score of June–September precipitation relative to state mean) interacted with competing news intensity (binary sports event indicator or continuous 0–1 index). **Data:** SHRUG VIIRS annual nightlights (2012–2021) at district level, NASA POWER monthly precipitation (2012–2021) at state centroids, hand-coded competing events calendar from public records. 5,024 district-years across 628 districts, 29 states, 8 years (2013–2020). **Method:** OLS with district and year fixed effects. Standard errors clustered at the state level (29 clusters). **Sample:** All rural and urban districts in major Indian states (excluding union territories with fewer than 3 districts). SDE = $\hat{\beta} \times \mathrm{SD}(X)/\mathrm{SD}(Y)$ for continuous treatment; $\hat{\beta}/\mathrm{SD}(Y)$ for binary treatment. Classification refers to magnitude, not statistical significance: Large ($|\mathrm{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).