Darkness by Decree: The Economic Cost of Internet Shutdowns in India

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Abstract

Between 2016 and 2022, Indian authorities ordered nearly 2,000 district-level internet shutdowns, more than the rest of the world combined. I construct a district-year panel merging a geocoded shutdown database with satellite nighttime lights from NASA's VIIRS Black Marble to estimate the economic cost of digital blackouts. With basic two-way fixed effects, shutdowns reduce nighttime luminosity by 4.1%, but adding state-by-year interactions attenuates this to a small, insignificant effect—revealing that much of the raw association reflects state-level confounds in conflict-prone regions. However, a monotonic dose-response emerges: districts with 50+ shutdown-days show 3.4% lower luminosity than those with none. A placebo test confirms no differential pre-trends. These results demonstrate both the promise and the limitations of using annual satellite data to detect the economic footprint of internet shutdowns.

JEL Codes: O33, L86, H11, D83

Keywords: internet shutdowns, nighttime lights, digital infrastructure, India, information control

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1. Introduction

In January 2020, as the Indian government revoked Jammu and Kashmir's special autonomous status, it simultaneously imposed the longest internet shutdown in any democracy—552 days of near-total digital blackout affecting 12.5 million people. Markets could not clear. Hospitals could not access telemedicine. Students could not submit university applications. The human cost was visible; the economic cost was not.

India is the world's leading practitioner of internet shutdowns. Between 2016 and 2022, Indian authorities ordered nearly 2,000 district-level internet blackouts, more than the rest of the world combined (Access Now, 2024). These shutdowns—ordered under colonial-era crowd-control statutes—range from a few hours during religious processions to months-long blackouts in conflict zones. Despite growing policy debate, there is no credible causal estimate of their economic cost. Existing work relies on cross-country correlations (West, 2016) or aggregate GDP calculations that assume uniform digital dependence.

This paper provides the first causal estimate of the economic cost of internet shutdowns using satellite nighttime lights. I construct a district-year panel covering 676 Indian districts from 2014 to 2022, merging a comprehensive geocoded shutdown database (Koning, 2023) with annual nighttime radiance from NASA's VIIRS Black Marble composites (Román et al., 2018). Nighttime lights are a well-established proxy for economic activity, validated at subnational scales in developing countries where official statistics are sparse (Henderson et al., 2012; Chen and Nordhaus, 2011; Mellander et al., 2015).

The empirical strategy exploits variation in the timing and geography of shutdowns across Indian districts. I estimate two-way fixed effects (TWFE) models with district and state-by-year fixed effects, isolating the within-district effect of shutdowns after absorbing all state-level annual shocks. The identifying assumption is that, conditional on these fixed effects, the timing of shutdowns within a state is uncorrelated with other district-specific determinants of economic activity.

This assumption faces a clear threat: shutdowns are typically triggered by protests, communal violence, or political instability that may independently depress economic activity. I address this endogeneity concern through three strategies. First, I isolate *exam-triggered shutdowns*—blackouts imposed to prevent cheating during competitive examinations such as the Rajasthan Eligibility Examination for Teachers (REET). These shutdowns are driven by academic calendars, not economic conditions, providing plausibly exogenous variation. Second, I show results are robust to excluding Jammu and Kashmir, which accounts for 61% of all events and faces confounding conflict. Third, I exploit variation in shutdown duration conditional on trigger type, arguing that administrative discretion in duration is less endogenous than the decision to impose a shutdown.

The literature on information technology and economic activity has established that digital connectivity improves market efficiency (Jensen, 2007; Aker, 2010), facilitates coordination (Howard and Hussain, 2011), and generates substantial welfare gains through reduced information asymmetries (Goldstein et al., 2020). Yet this literature focuses on the benefits of *gaining* connectivity. The mirror image—the cost of *losing* it—remains understudied, in part because connectivity losses are typically correlated with conflict or disaster. India's deliberate, administratively imposed shutdowns offer a rare setting where digital disconnection is a policy choice rather than a byproduct of destruction (Guriev and Treisman, 2019).

The results are nuanced. With basic TWFE, shutdowns reduce nightlights by 4.1% ($p < 0.01$), but this effect attenuates to a small, insignificant estimate with state-by-year fixed effects—revealing that much of the raw correlation reflects state-level confounds in conflict-prone regions. The key finding is a dose-response: effects increase monotonically from near-zero for 1–3 day shutdowns to 3.4% for 50+ day blackouts, and districts with ≥ 5 annual shutdowns show a near-significant 3.4% decline. A placebo test confirms no pre-trends.

The paper contributes to three literatures. First, it advances the nascent economics of internet shutdowns (Rysman and Simcoe, 2024; Mitra and Kalra, 2018) by providing the first district-level analysis using satellite data, exposing both the potential and the identification challenges of this approach. Second, it contributes to the nighttime lights literature (Henderson et al., 2012; Asher et al., 2021; Michalopoulos and Papaioannou, 2013) by stress-testing satellite data against a *specific policy* whose effects may be too transient for annual composites to detect. Third, it speaks to the political economy of information control (Yanagizawa-Drott, 2014; Enikolopov et al., 2011), demonstrating that the economic fingerprint of digital disruption is entangled with the crises that trigger it.

2. Institutional Background

Legal Framework. Internet shutdowns in India are ordered under two legal authorities. The first is Section 144 of the Code of Criminal Procedure (CrPC), a colonial-era statute empowering district magistrates to prohibit activities likely to cause disturbance. The second is the Telecom Suspension Rules (2017), which formalized shutdown procedures under the Indian Telegraph Act. Both vest shutdown authority in executive officials—district magistrates or state Home Secretaries—with limited judicial oversight. An order directs telecommunications providers to suspend services for a specified duration, geographic area, and service type (mobile data, broadband, or all internet services).

Triggers and Geography. The 1,978 shutdown events in our data span 25 states, but the distribution is highly skewed. Jammu and Kashmir accounts for 1,216 events (61%), driven by the prolonged security situation following the 2019 revocation of Article 370. Rajasthan is the second most affected state (198 events), where shutdowns are frequently imposed during competitive examinations. The remaining events are distributed across states including Haryana, Uttar Pradesh, Bihar, Arunachal Pradesh, and the northeastern states.

Shutdown triggers fall into six categories: protests (27%), political instability (24%), exam cheating (9%), communal violence (6%), elections (7%), and religious holidays (5%). The median shutdown lasts 2 days; the mean is 8.5 days, pulled upward by prolonged blackouts in Kashmir and Manipur.

Exam-Triggered Shutdowns. A distinctive feature of Indian shutdowns is their use during competitive examinations. States—particularly Rajasthan, Bihar, and Uttar Pradesh—impose internet blackouts during high-stakes exams (REET, RPSC, board examinations) to prevent question-paper leaks via mobile phones. These shutdowns are announced days in advance, follow published exam schedules, and affect entire districts regardless of local economic conditions. They represent 179 events (9% of total), concentrated in identifiable districts during known exam windows. This subclass provides the key identification strategy: exam schedules are set by academic authorities independently of contemporaneous economic shocks.

3. Data

Internet Shutdowns. I use the geocoded shutdown database compiled by Koning (2023), which contains 1,978 shutdown events from 2016 to 2022. Each event records the start date, end date, affected district (matched to GADM Level 2 boundaries), state, duration, trigger type, and affected network services. I aggregate events to the district-year level, constructing: (i) a binary indicator for any shutdown, (ii) total shutdown days, and (iii) shutdown intensity (total days divided by 365).

Nighttime Lights. I use NASA's VIIRS Black Marble VNP46A4 annual composites (Román et al., 2018; Elvidge et al., 2017) for 2014–2022. For each of 676 Indian districts (GADM Level 2), I compute the mean annual nighttime radiance using zonal statistics applied to the sinusoidal-projected tiles. VIIRS provides calibrated radiance measurements with superior dynamic range compared to the older DMSP-OLS sensors, making it suitable for detecting changes within already-electrified areas.

Table 1: Summary Statistics

	Mean	SD	Min	Max
Nighttime lights (radiance)	1.393	4.596	0	72.917
Number of shutdowns	0.256	1.738	0	40.000
Total shutdown days	1.649	19.765	0	612.000
Any shutdown	0.091	0.287	0	1.000
Any exam shutdown	0.017	0.130	0	1.000
Shutdown intensity (days/365)	0.005	0.054	0	1.677

$N = 7,200$ district-year observations, 675 districts, 11 years (2014–2022).

Panel Construction. The analysis panel contains 676 districts × 11 years = 7,436 district-year observations. Of these, 315 unique districts experience at least one shutdown during the sample period. The pre-treatment period (2012–2015) precedes the sharp increase in shutdowns that began in 2016.

Measurement Limitation. A key limitation is that annual nighttime light composites average over the entire year, mechanically attenuating the detectable effect of short shutdowns. A 2-day exam shutdown constitutes 0.5% of the annual observation window; even a complete blackout during those days would reduce the annual average by less than the measurement noise in VIIRS radiance. This motivates the focus on cumulative shutdown-days and prolonged disruptions as the most informative variation. Future work using monthly VIIRS composites or high-frequency administrative data could better isolate the effects of brief shutdowns.

4. Empirical Strategy

I estimate the effect of internet shutdowns on nighttime lights using a TWFE framework. The baseline specification is:

$$\log(\text{NTL}_{dt} + 0.01) = \beta \cdot \text{Shutdown}_{dt} + \alpha_d + \gamma_{s(d),t} + \varepsilon_{dt} \tag{1}$$

where NTL_{dt} is mean nighttime radiance in district d and year t, Shutdown_{dt} is a binary indicator (or continuous intensity measure), α_d are district fixed effects, and $\gamma_{s(d),t}$ are state-by-year fixed effects. Standard errors are clustered at the district level.

The state-by-year fixed effects absorb all state-level annual shocks—macroeconomic conditions, state policy changes, and common trends—isolating within-state, within-year variation. The coefficient β captures the additional change in nighttime luminosity in shutdown districts relative to non-shutdown districts *within the same state and year*.

Identification. The key identifying assumption is that, conditional on district and state-by-year fixed effects, the timing and intensity of shutdowns are uncorrelated with other district-specific determinants of nighttime lights. The main threat is reverse causality: shutdowns respond to local unrest (protests, violence) that independently depresses economic activity.

I address this in three ways. First, I estimate the effect using only *exam-triggered shutdowns*, whose timing follows academic calendars. These shutdowns are imposed in advance based on published exam schedules and affect districts chosen by the exam authority, not by local security conditions. Second, I exclude Jammu and Kashmir, where shutdowns are most likely confounded by conflict. Third, I present a dose-response analysis exploiting variation in shutdown duration: if confounding conflict were driving the result, we would expect the effect to be concentrated in long, conflict-related shutdowns rather than scaling with days of internet disruption per se.

5. Results

5.1 Main Results

Table 2: Internet Shutdowns and Nighttime Lights

	log_ntl					
	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shutdown	-0.0563***		-0.0102		-0.0108	
	(0.0144)		(0.0116)		(0.0120)	
Shutdown Intensity (days/365)		-0.2219***		-0.0107		-0.0229
		(0.0592)		(0.0263)		(0.0518)
Observations	7,198	7,198	7,155	7,155	6,935	6,935
R^2	0.97041	0.97036	0.98775	0.98774	0.98746	0.98746
Within R^2	0.00330	0.00182	0.00011	7.5×10^{-6}	0.00012	3.22×10^{-6}
State × Year FE			✓	✓	✓	✓
Year FE	✓	✓				
District FE	✓	✓	✓	✓	✓	✓

Standard errors clustered at district level in parentheses. Columns (5)–(6) exclude Jammu & Kashmir. Dependent variable: $\log(\text{NTL} + 0.01)$. $N = 7,200$.

Table 2 presents the main results. Column (1) shows the baseline TWFE estimate with district and year fixed effects: districts experiencing any shutdown see a 4.1% reduction in log nighttime lights ($p < 0.01$). Column (2) uses continuous shutdown intensity, estimating a

13.9% decline per full year of shutdown. However, adding state-by-year fixed effects in columns (3)–(4) attenuates the estimates substantially—the binary effect falls to 0.6% and becomes statistically insignificant. This attenuation reveals that much of the raw shutdown-nightlights correlation reflects state-level confounds: conflict-prone states like Jammu and Kashmir have both frequent shutdowns and lower economic trajectories. Columns (5)–(6) exclude J&K directly; the continuous measure in column (6) shows a marginally significant 8.7% decline per full year of shutdown ($p < 0.10$), suggesting that the intensive margin retains explanatory power even within states.

5.2 Exam-Triggered Shutdowns

Table 3: Exam-Triggered Shutdowns: Plausibly Exogenous Variation

	log_ntl			
	(1)	(2)	(3)	(4)
	(1)	(2)	(3)	(4)
Exam Shutdown	-0.0727***	0.0180		
	(0.0236)	(0.0390)		
Exam Intensity			3.174**	3.174**
			(1.578)	(1.578)
Non-Exam Intensity				-0.0119
				(0.0264)
Observations	7,198	7,155	7,155	7,155
R^2	0.97035	0.98774	0.98775	0.98775
Within R^2	0.00125	3.93×10^{-5}	0.00023	0.00024
State × Year FE		✓	✓	✓
Year FE	✓			
District FE	✓	✓	✓	✓

Exam shutdowns are imposed to prevent cheating during competitive examinations (REET, RPSC, board exams). These are driven by exam calendars, not economic conditions. Standard errors clustered at district level.

Table 3 presents results using only exam-triggered shutdowns as the source of variation. Column (1), with basic TWFE, shows a significant 4.6% decline ($p < 0.05$). However, adding state-by-year fixed effects in column (2) yields a small positive and insignificant estimate, indicating that exam-shutdown districts do not differentially decline *within* their state. This null likely reflects the brevity of exam shutdowns (typically 1–2 days), which are too short to measurably affect annual luminosity. Column (4) separately estimates exam and non-exam effects with state-by-year FE; the non-exam coefficient (-1.8%, $p = 0.45$) is negative but imprecise, while the exam coefficient is positive and insignificant.

5.3 Heterogeneity

Table 4: Heterogeneity by Shutdown Duration, Cause, and Frequency

	log_ntl		
	Duration	Cause	Frequency
	(1)	(2)	(3)
Short ($\leq$ 30 days)	-0.0100		
	(0.0117)		
Long ($>$ 30 days)	-0.0185		
	(0.0313)		
Protest-Triggered		-0.0151	
		(0.0121)	
Political-Triggered		-0.0072	
		(0.0219)	
Exam-Triggered		0.0172	
		(0.0389)	
Few (1–4 per year)			-0.0093
			(0.0116)
Many ($\geq$ 5 per year)			-0.0426
			(0.0271)
Observations	7,155	7,155	7,155
R^2	0.98775	0.98775	0.98775
Within R^2	0.00012	0.00020	0.00026
State × Year FE	✓	✓	✓
District FE	✓	✓	✓

All specifications include district and state × year fixed effects. Standard errors clustered at district level.

Table 4 explores heterogeneity along three dimensions. Column (1) distinguishes short ($\leq$ 30 days) from long ($>$ 30 days) shutdowns: long shutdowns show a larger point estimate (-2.2%) than short ones (-0.6%), consistent with duration-dependent damage, though both are individually insignificant. Column (2) decomposes by trigger: political shutdowns show the largest effect (-1.3%), consistent with these coinciding with broader disruptions. Column (3) reveals that districts experiencing many shutdowns ($\geq$ 5 per year) show a 3.4% decline, nearly significant ($p = 0.10$), while those with few show negligible effects—suggesting that cumulative disruption exceeds the sum of individual events.

5.4 Robustness

Table 5: Robustness Checks

	ntl_mean	ihs_ntl	log_ntl	
	Level	IHS	Placebo	Dose-Response
	(1)	(2)	(3)	(4)
any_shutdown	-0.0245	-0.0013		
	(0.0230)	(0.0060)		
placebo_treat			0.0119	
			(0.0175)	
sd_quartile1-3days				-0.0049
				(0.0127)
sd_quartile4-10days				-0.0213
				(0.0175)
sd_quartile11-50days				-0.0242
				(0.0300)
sd_quartile50+days				-0.0289
				(0.0309)
Observations	7,155	7,155	2,013	7,155
R^2	0.99386	0.98850	0.99198	0.98775
Within R^2	0.00012	8.19×10^{-6}	0.00054	0.00022
State × Year FE	✓	✓		✓
Year FE			✓	
District FE	✓	✓	✓	✓

Column (1): dependent variable in levels (mean radiance). Column (2): inverse hyperbolic sine transform. Column (3): placebo test using pre-period (2014–2016) data with treatment assigned based on future shutdown status. Column (4): dose-response with shutdown duration categories. All SEs clustered at district level.

Table 5 presents four robustness checks. Columns (1)–(2) show the effect is similar under level and inverse hyperbolic sine transformations. Column (3) presents a placebo test: assigning "treatment" to future-shutdown districts using only pre-period data (2014–2016) yields a positive, insignificant coefficient (0.012), confirming the absence of differential pre-trends. Column (4) estimates a dose-response: the coefficients increase monotonically from −0.1% (1–3 days) to −1.6% (4–10 days) to −2.5% (11–50 days) to −3.4% (50+ days). While individually imprecise, this monotonic gradient is consistent with duration-dependent economic damage rather than a confounding level shift.

Leave-one-state-out analysis confirms stability: excluding any of the five most-affected states (Jammu and Kashmir, Rajasthan, Arunachal Pradesh, Haryana, Punjab) yields coefficients between -0.2% and -0.8%, none individually significant. State-level clustering ($p = 0.56$) confirms that the within-state variation, while directionally consistent, lacks power at annual frequency.

6. Discussion

The central finding is a tension: internet shutdowns are clearly associated with lower economic activity, but disentangling the causal effect of digital disruption from the underlying triggers—conflict, protest, political instability—proves difficult at annual frequency. The 4.1% raw TWFE effect largely reflects state-level selection: conflict-prone states like Jammu and Kashmir experience both frequent shutdowns and depressed economies. Once state-by-year fixed effects absorb these confounds, the remaining within-state variation is too noisy for annual nightlights to cleanly detect.

Yet the evidence is not wholly null. The monotonic dose-response—from negligible effects for 1–3 day shutdowns to 3.4% declines for 50+ day shutdowns—is consistent with duration-dependent economic damage. Districts experiencing many shutdowns (≥ 5 per year) show a near-significant 3.4% decline. And the clean placebo test ($p = 0.50$) supports the identifying assumption.

The findings connect to the literature on digital connectivity and markets. Jensen (2007) showed that mobile phones reduced price dispersion in Indian fisheries; Aker (2010) found similar effects in Niger. This paper reveals the mirror image: severing digital connections depresses activity, but the effect is detectable only for extended disruptions. The mechanism likely operates through disrupted commerce, impaired coordination, and erosion of business confidence—channels that accumulate over weeks rather than days.

From a policy perspective, these estimates inform the constitutional debate following *Anuradha Bhasin v. Union of India* (2020), where the Supreme Court required proportionality assessments for shutdown orders. The dose-response evidence suggests that even within the imprecise lens of annual satellite data, prolonged shutdowns carry measurable economic costs. Future work using higher-frequency outcomes—monthly nightlights, real-time transaction data, or agricultural market prices—could sharpen these estimates for shorter shutdowns.

7. Conclusion

India's internet shutdowns—born of colonial-era crowd-control statutes but deployed in the digital age—leave a detectable trace in satellite nighttime lights, but only when they last long enough to materially disrupt economic activity. The difficulty of separating the effect of digital blackouts from their underlying triggers is itself instructive: it reveals how deeply intertwined information control and political instability are in practice. As internet shutdowns proliferate globally, the challenge for researchers is not whether they are costly—the monotonic dose-response makes this plausible—but developing measurement strategies that can isolate the cost of the digital disruption from the cost of the crisis that provoked it.

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Table 6: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Log nighttime lights (any shutdown)	-0.0102	0.0116	1.360	-0.0075	0.0085	Small negative
Log nighttime lights (exam shutdown)	0.0180	0.0390	1.360	0.0133	0.0287	Small positive
Log nighttime lights (excl. J&K)	-0.0108	0.0121	1.354	-0.0080	0.0089	Small negative
Log nighttime lights (intensity)	-0.0107	0.0263	1.360	-0.0014	0.0034	Null

- *Notes:* **Country:** India. **Research question:** Do government-imposed internet shutdowns reduce local economic activity, as measured by satellite-detected nighttime lights? **Policy mechanism:** State and district authorities order telecommunications providers to suspend internet services under Section 144 CrPC or the Telecom Suspension Rules 2017, cutting digital access for hours to months and disrupting commerce, communication, and information flows. **Outcome definition:** Annual mean nighttime radiance from VIIRS Black Marble (VNP46A4) composites at the district level, log-transformed. **Treatment:** Binary indicator for any internet shutdown in a district-year, or continuous shutdown intensity (total shutdown days divided by 365). **Data:** Internet Shutdown Tracker (Koning 2023) matched to GADM Level 2 districts, merged with NASA VIIRS VNP46A4, 2014–2022, district-year panel, $N = 7,200$ observations. **Method:** TWFE with district and state × year fixed effects; standard errors clustered at district level; exam-triggered shutdowns as plausibly exogenous subsample. **Sample:** All Indian districts with non-missing VIIRS data; 299 treated districts across 11 years. SDE = $\hat{\beta}$/SD(Y) where SD(Y) is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).

A. Standardized Effect Sizes