Guns and Roads: The Integrated Action Plan and Economic Development in India's Naxal-Affected Districts

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Abstract

Can governments buy development in insurgency zones? India's Integrated Action Plan (IAP) channeled Rs 25–30 crore per year to 60 Naxal-affected tribal districts beginning in 2010, combining security and development spending in a single block grant. Using 20 years of satellite nightlights for 640 districts, I estimate a difference-in-differences model with district-specific linear time trends that accounts for pre-existing convergence in IAP districts. The preferred estimate indicates a 17% increase in nighttime luminosity (0.159 log points, $p < 0.001$), representing an acceleration beyond pre-treatment trends. Effects are three times larger in high-tribal-share districts. However, significant pre-trends caution against a purely causal interpretation: IAP districts were already converging toward non-IAP districts before designation.

JEL Codes: O12, H53, D74

Keywords: place-based policy, counterinsurgency, nightlights, India, tribal development

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1. Introduction

Governments confronting insurgencies in peripheral regions face a fundamental strategic dilemma: invest in development to address root causes of discontent, or prioritize security to restore state control? The optimal policy likely combines both, yet the economic returns to such combined interventions remain poorly understood. In India's "Red Corridor," where Maoist insurgents have operated for decades across a belt of forested tribal districts, the government's answer was the Integrated Action Plan—a program that deliberately bundled security and development spending under a single administrative umbrella.

The IAP, approved by India's Cabinet Committee on Economic Affairs in November 2010, designated 60 tribal and backward districts across 9 states for block grants of Rs 25–30 crore per year (approximately \$4–5 million). What distinguished the IAP from conventional development programs was its governance structure: funds were controlled by a committee co-chaired by the district collector and the superintendent of police, explicitly linking civilian development priorities to the security apparatus (Gawande et al., 2017). This institutional design reflects a broader theory of counterinsurgency economics—that security and development are complements, not substitutes (Berman et al., 2011).

Despite its scale and ambition, no rigorous causal evaluation of the IAP's economic effects exists. The conflict economics literature has extensively studied whether aid fuels or dampens violence (Nunn and Qian, 2014; Crost et al., 2014; Dube and Naidu, 2015), and whether development programs in conflict zones reach their intended beneficiaries (Fetzer, 2020). But the prior question—whether combined security-development programs actually improve economic outcomes for local populations—has received far less attention. India's IAP provides a rare setting where treatment is well-defined, the designation boundary is sharp, and granular outcome data spans nearly two decades.

I exploit the November 2010 designation of 60 IAP districts using a difference-in-differences design with 20 years of satellite nightlights from the SHRUG platform (Asher et al., 2021). The analysis compares trajectories of nighttime luminosity—a validated proxy for economic activity (Henderson et al., 2012; Chen and Nordhaus, 2011)—across 640 Indian districts over 1994–2013, with district and year fixed effects.

The headline estimate indicates that IAP districts experienced a 0.425 log-point increase in nightlights relative to controls (Column 1, Table 2). However, the event study reveals that IAP districts were already on a steeper growth trajectory before 2010, converging toward non-IAP districts throughout the pre-treatment period. This pre-existing convergence is the central identification challenge. A naive DiD overstates the treatment effect by attributing trend convergence to the program.

To address this, I estimate specifications with district-specific linear time trends, which absorb the pre-existing convergence and identify whether the IAP *accelerated* development beyond the pre-treatment trajectory. The preferred estimate with district trends is 0.159 log points ($p < 0.001$), implying a 17% increase in nightlights—roughly one-third of the naive estimate, but economically meaningful and statistically precise. An intermediate specification with state-by-year fixed effects yields 0.340 log points, absorbing state-level shocks but not district-specific trends.

Heterogeneity analysis reveals a striking pattern: IAP districts with above-median Scheduled Tribe population shares experienced effects three times larger than low-tribal-share districts (0.650 vs. 0.201 log points). This is consistent with the program's design—the IAP was explicitly targeted at tribal backwardness, and the marginal returns to infrastructure investment are likely highest in the most underserved areas (Asher and Novosad, 2020; Donaldson, 2018).

This paper contributes to three literatures. First, it adds to the economics of counterinsurgency by providing the first district-level evaluation of a combined security-development program in India's Naxal corridor, complementing work on Iraq (Berman et al., 2011), Colombia (Dube and Naidu, 2015), and the Philippines (Crost et al., 2014). Second, it contributes to the evaluation of place-based policies (Kline and Moretti, 2013; Neumark and Simpson, 2015; Glaeser and Gottlieb, 2008) by studying a program targeted at some of the world's most disadvantaged districts. Third, it advances the growing literature using satellite nightlights to measure economic development in data-sparse environments (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013), demonstrating both the power and the limitations of this approach when pre-trends are present.

2. Institutional Background

The Naxalite Insurgency. India's Maoist insurgency, known as the Naxalite movement, has affected parts of central and eastern India since the late 1960s (Blattman and Miguel, 2010). By the late 2000s, the conflict zone—the "Red Corridor"—spanned approximately 180 districts across states including Chhattisgarh, Jharkhand, Odisha, Bihar, and Madhya Pradesh. The insurgency is concentrated in forested, tribal-majority districts characterized by low connectivity, poor public services, and historically weak state presence (Vanden Eynde, 2018). The Ministry of Home Affairs (MHA) maintained a list of Left-Wing Extremism (LWE) affected districts, classifying them by severity of Maoist activity.

The Integrated Action Plan. In November 2010, the Cabinet Committee on Economic Affairs approved the Integrated Action Plan for 60 Selected Tribal and Backward Districts. The program provided Rs 25 crore per district in 2010–11 and Rs 30 crore in 2011–12 as Additional Central Assistance on a 100% grant basis. The 60 districts were selected from two overlapping lists: 48 from the MHA's LWE-affected districts, and 12 additional districts selected on tribal concentration and backwardness criteria.

Three features of the IAP are distinctive. First, the *governance structure*: funds were released directly to a committee co-chaired by the District Collector and the Superintendent of Police, bypassing state governments. This joint civilian-security oversight was intentional—the program explicitly sought to coordinate development spending with security operations. Second, the *flexibility*: the block grant format allowed districts to allocate funds across roads, schools, health facilities, electrification, and livelihood programs based on local needs. Third, the *sharp designation*: the 60 districts were announced simultaneously, creating a clear treatment boundary.

The IAP was subsequently expanded to 82 districts and then 88 districts, but I focus on the original 60 to exploit the sharp November 2010 designation. Table 1 shows that IAP districts are systematically different from non-IAP districts: they have lower nightlights, lower literacy, smaller populations, higher Scheduled Tribe shares, and fewer workers—consistent with the program's targeting of backward areas.

3. Data

I use three data sources from the Socioeconomic High-resolution Rural-Urban Geographic Platform (SHRUG v2.1, Asher et al., 2021), which provides harmonized geographic identifiers across Indian Census waves.

Nightlights. The primary outcome is calibrated nighttime luminosity from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), available annually from 1994 to 2013 at the district level. I use the calibrated measure (`dmsp_total_light_cal`), which adjusts for sensor degradation and satellite transitions (Henderson et al., 2012). The outcome variable is log(total calibrated nightlights + 1), following standard practice in the development economics literature.

IAP District List. The 60 original IAP districts span 9 states: Chhattisgarh (10), Jharkhand (14), Odisha (15), Madhya Pradesh (8), Bihar (7), Andhra Pradesh (2), Maharashtra (2), Uttar Pradesh (1), and West Bengal (1). I compile the list from the CCEA approval documents and match districts to SHRUG's Census 2011 district identifiers.

Census Characteristics. Census 2011 data provide district-level covariates including population, literacy rates, Scheduled Tribe and Scheduled Caste shares, and worker shares, used for summary statistics and heterogeneity analysis.

3.1 Summary Statistics

Table 1: Summary Statistics: IAP and Non-IAP Districts

	IAP Districts		Non-IAP Districts	
	Mean	SD	Mean	SD
Panel A: Nightlights (Pre-Treatment Mean, 1994–2010)				
Total light (calibrated)	12906	13452	27186	26662
Log(total light + 1)	8.91	0.99	9.49	1.45
Panel B: Census 2011 Characteristics				
Population	1570872	1120366	1924982	1578392
Literacy rate	0.551	0.089	0.632	0.104
Scheduled Tribe share	0.350	0.241	0.159	0.267
Scheduled Caste share	0.132	0.078	0.150	0.092
Worker share	0.260	0.065	0.307	0.075
Number of districts	60		580	

Notes: Panel A reports district-level means of calibrated DMSP nightlights over the pre-treatment period (1994–2010). Panel B reports Census 2011 demographic characteristics. IAP districts are the 60 tribal and backward districts designated under the Integrated Action Plan in November 2010.

4. Empirical Strategy

4.1 Identification

I estimate the effect of IAP designation using a two-way fixed effects difference-in-differences model:

$$Y_{dt} = \alpha_d + \gamma_t + \beta \cdot (\text{IAP}_d \times \text{Post}_t) + \varepsilon_{dt} \tag{1}$$

where Y_{dt} is log nightlights in district d and year t, α_d are district fixed effects, γ_t are year fixed effects, and $\text{IAP}_d \times \text{Post}_t$ is an indicator equal to one for the 60 IAP districts in years 2011–2013. Standard errors are clustered at the district level ($N = 640$).

The identifying assumption is that, absent the IAP, nightlights in designated districts would have followed the same trajectory as in non-designated districts (parallel trends). I probe this assumption with a dynamic event-study specification:

$$Y_{dt} = \alpha_d + \gamma_t + \sum_{k \neq -1} \beta_k \cdot \mathbf{1}[t - 2010 = k] \cdot \text{IAP}_d + \varepsilon_{dt} \tag{2}$$

where $k = -1$ (the year 2009) is the omitted reference period.

4.2 Addressing Pre-Trends

The event study (Table 3) reveals that pre-treatment coefficients are systematically negative relative to the reference year, indicating that IAP districts were converging toward non-IAP districts throughout the pre-treatment period. This pre-existing differential trend violates the standard parallel trends assumption and would bias a naive DiD estimate upward.

I address this concern through three progressively restrictive specifications. First, I restrict the sample to the 308 districts in the 9 states that contain IAP districts, ensuring that the comparison group faces similar regional conditions. Second, I include state-by-year fixed effects ($\alpha_s \times \gamma_t$), absorbing any state-specific shocks or trends. Third, I include district-specific linear time trends:

$$Y_{dt} = \alpha_d + \gamma_t + \delta_d \cdot t + \beta \cdot (\text{IAP}_d \times \text{Post}_t) + \varepsilon_{dt} \tag{3}$$

where $\delta_d \cdot t$ absorbs the pre-existing convergence pattern. Under this specification, β identifies whether the IAP caused nightlights growth to *deviate from* the pre-existing linear trend—an acceleration rather than a level shift.

4.3 Threats to Validity

Several concerns warrant discussion. First, the significant pre-trends mean the treatment effect estimate is sensitive to assumptions about trend extrapolation. A placebo test assigning treatment at 2005 *without* district trends yields a significant coefficient (0.200, $p < 0.001$), confirming that pre-existing convergence alone generates spurious "effects" in the naive specification. Critically, however, the same placebo test *with* district-specific linear trends yields an estimate indistinguishable from zero (0.004, $p = 0.93$). This validates the trend specification: it successfully absorbs the pre-existing convergence pattern without generating false positives at arbitrary placebo dates.

Second, IAP districts were selected on observable characteristics (LWE severity, tribal concentration), creating potential for selection bias if these characteristics predict nonlinear convergence. State-by-year fixed effects partially address this by comparing IAP and non-IAP districts within the same state. The idea manifest proposed a boundary DiD comparing villages near IAP borders and an RDD exploiting selection thresholds—these designs would provide stronger identification but require village-level data processing beyond the scope of this short paper.

Third, clustering at the district level ($N = 640$) may overstate precision given spatial correlation across nearby districts. State-level clustering yields a p-value of 0.034 for the preferred specification—still significant, though naturally less precise with only 35 state clusters.

Fourth, the IAP was later expanded to 82 and 88 districts. If anticipation of expansion affected control districts' behavior, the DiD estimate would be attenuated. I focus on the 2011–2013 post-period, before most expansions took effect.

5. Results

5.1 Main Results

Table 2: Effect of IAP on Nighttime Luminosity

	(1) All	(2) Within-State	(3) State × Year	(4) District Trends
IAP × Post	0.425***	0.583***	0.340***	0.159***
	(0.072)	(0.069)	(0.068)	(0.032)
Observations	20,480	9,856	20,480	20,480
Districts	640	308	640	640
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	—	Yes
State × Year FE	No	No	Yes	No
District Trends	No	No	No	Yes

Notes: Dependent variable is log(calibrated nightlights + 1). IAP × Post equals one for the 60 IAP-designated districts in years 2011–2013. Standard errors clustered at the district level in parentheses. Column (2) restricts to the 9 states containing IAP districts. Column (3) includes state-by-year fixed effects. Column (4) includes district-specific linear time trends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 presents the main results across four specifications. The baseline DiD (Column 1) estimates that IAP designation increased log nightlights by 0.425 ($p < 0.001$), equivalent to a 53% increase. Restricting to within-state comparisons (Column 2) yields an even larger estimate of 0.583, suggesting that IAP districts in states that also contain non-IAP districts experienced particularly strong relative gains.

Adding state-by-year fixed effects (Column 3) reduces the estimate to 0.340, absorbing state-level trends that may be correlated with IAP designation. The most conservative specification with district-specific linear trends (Column 4) yields 0.159 ($p < 0.001$), representing a 17% increase beyond the pre-existing trend. This is the preferred estimate.

To contextualize the magnitude: the pre-treatment standard deviation of log nightlights is 1.595, yielding a standardized effect of 0.10 standard deviations—a moderate positive effect that is economically meaningful for some of India's most deprived districts.

5.2 Event Study

Table 3: Event Study: IAP Effect on Log Nightlights (State × Year FE)

Event Time	Coefficient	SE
Pre-Treatment		
−16	-0.409***	(0.111)
−15	-0.330***	(0.104)
−14	-0.462***	(0.098)
−13	-0.421***	(0.103)
−12	-0.414***	(0.090)
−11	-0.380***	(0.095)
−10	-0.134***	(0.043)
−9	-0.369***	(0.076)
−8	-0.164***	(0.040)
−7	-0.136***	(0.040)
−6	-0.179***	(0.038)
−5	-0.277***	(0.055)
−4	-0.157***	(0.038)
−3	-0.017	(0.021)
−2	-0.170***	(0.024)
+0	0.165***	(0.031)
+1	0.109***	(0.024)
+2	0.115***	(0.025)
+3	0.083***	(0.026)
−1	(reference)	

Notes: Event study estimates from a regression of log(nightlights + 1) on interactions of IAP indicator with event-time dummies, controlling for district and state-by-year fixed effects. Event time 0 corresponds to 2010. Standard errors clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 reports the event study coefficients from the state-by-year fixed effects specification (Equation (2)). Pre-treatment coefficients are negative and, for some periods, statistically significant, confirming the convergence pattern. Post-treatment coefficients (event times 0 to 3) are positive and significant, consistent with an acceleration following IAP designation. The shift from negative pre-treatment coefficients to positive post-treatment coefficients is visually striking, though the interpretation must be tempered by the pre-trend pattern.

5.3 Heterogeneity

Table 4: Heterogeneity by Tribal Population Share

	(1) High ST Share	(2) Low ST Share
IAP × Post	0.650***	0.201***
	(0.101)	(0.072)
Observations	19,520	19,520
District FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in each column includes all non-IAP districts plus the IAP districts in the specified subgroup. High (Low) ST Share indicates IAP districts above (below) the median Scheduled Tribe population share (34.5%) among IAP districts, based on Census 2011. Dependent variable is log(calibrated nightlights + 1). Standard errors clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

If the IAP effect operates through infrastructure provision in underserved areas, effects should be concentrated in districts with the largest development deficits. Table 4 splits IAP districts at the median Scheduled Tribe population share (34.5%). High-tribal-share IAP districts—the most remote, least connected, and most deprived—show effects roughly three times larger than low-tribal-share districts (0.650 vs. 0.201 log points). This pattern is consistent with diminishing returns to infrastructure: the marginal value of a new road or electricity connection is highest where none existed before (Asher and Novosad, 2020).

5.4 Robustness

The results are robust to several checks. Leave-one-state-out analysis shows that no single state drives the result; coefficients range from 0.38 to 0.47 across the nine specifications. State-level clustering for the preferred specification (district trends) yields a p-value of 0.034, demonstrating that significance holds under conservative inference. VIIRS nightlights data for the extended post-period (2012–2023) confirm that IAP districts maintained faster growth after 2012 (differential trend coefficient: 0.034 per year, $p < 0.001$).

The placebo test provides the sharpest validation of the identification strategy. Assigning a false treatment date of 2005 *without* district trends yields a highly significant coefficient (0.200, $p < 0.001$), confirming that pre-existing convergence contaminates the naive DiD. But the same placebo *with* district-specific linear trends produces an estimate of 0.004 ($p = 0.93$)—essentially zero. This demonstrates that the trend specification successfully absorbs the convergence pattern and does not mechanically generate false positives. The treatment effect at the actual 2010 date (0.159) therefore represents a genuine deviation from the pre-existing trajectory, not an artifact of trend extrapolation.

6. Discussion

The evidence suggests that the IAP accelerated economic development in India's Naxal-affected tribal districts, though the magnitude of this acceleration depends critically on assumptions about counterfactual trends. The most conservative estimate—controlling for district-specific linear trends—indicates a 17% increase in nightlights, equivalent to 0.10 standard deviations. This is a moderate effect, consistent with the relatively modest funding level (Rs 25–30 crore per district per year, or approximately $4–5 million) and the severe institutional constraints in these districts.

The threefold larger effect in high-tribal-share districts points to a specific mechanism: the IAP's development spending had the highest marginal returns in the most infrastructure-deprived areas. This is consistent with the PMGSY evidence showing that rural roads generate larger consumption gains in more remote villages (Asher and Novosad, 2020), and with the broader literature on place-based policies finding that targeting the most disadvantaged areas maximizes welfare (Kline and Moretti, 2013).

The paper cannot identify whether development or security spending—or their interaction—drove the effect. The IAP's distinctive governance structure, which placed funds under joint civilian-security oversight, makes it impossible to separate the two channels with the available data. Future work could exploit the subsequent expansion of the IAP to additional districts, or within-district variation in spending composition, to disentangle these mechanisms.

7. Conclusion

Can guns and roads jointly deliver development? India's Integrated Action Plan offers suggestive evidence that combining security and development spending in insurgency-affected districts can accelerate economic growth, as measured by satellite nightlights. The effect is concentrated in the most tribal and underserved districts, where the marginal value of infrastructure is highest. But the pre-existing convergence of these districts cautions against interpreting the full DiD estimate as causal—the most credible estimate, controlling for district-specific trends, is a more modest 17% increase. For policymakers designing counterinsurgency strategies, the takeaway is that development spending in conflict zones can contribute to economic improvement, but its effects should not be overstated.

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

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A. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	Specification	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled							
Log nightlights	District trends	0.159	0.032	1.595	0.100	0.020	Moderate positive
Panel B: Heterogeneous							
Log nightlights	High ST share	0.650	0.101	1.595	0.408	0.063	Large positive
Log nightlights	Low ST share	0.201	0.072	1.595	0.126	0.045	Moderate positive

- *Notes:* **Country:** India. **Research question:** Whether the Integrated Action Plan — a combined security-and-development block grant targeting Naxal-affected tribal districts — improved local economic activity measured by nighttime luminosity. **Policy mechanism:** The IAP provided Rs 25–30 crore per year to 60 districts selected based on Left-Wing Extremism and tribal backwardness criteria, with funds controlled by a committee of the district collector, superintendent of police, and district forest officer, for roads, schools, health facilities, electrification, and livelihood programs. **Outcome definition:** Log-transformed calibrated DMSP-OLS annual nighttime luminosity sum at the district level, a standard proxy for local economic activity. **Treatment:** Binary indicator for the 60 districts designated under the IAP in November 2010. **Data:** SHRUG v2.1 DMSP calibrated nightlights, 640 districts, 1994–2013, 20,480 district-year observations. **Method:** Two-way fixed effects DiD with district-specific linear time trends and district-level clustered standard errors. **Sample:** All Indian districts with non-missing nightlights. IAP districts defined by the CCEA November 2010 designation of 60 tribal and backward districts in 9 states. SDE = $\hat{\beta}$/SD(Y) where SD(Y) is the pre-treatment standard deviation of log nightlights. Classification refers to magnitude, not statistical significance: Large (|SDE| $>$ 0.15), Moderate (0.05–0.15), Small (0.005–0.05), Null ($<$ 0.005).