



## NIGHT-TIME LIGHTS, ECONOMIC ACTIVITY AND ELECTORAL ACCOUNTABILITY IN INDIA (2014–2024)

Shivam Chauhan

### RESEARCH ARTICLE



#### Author Details:

Research Scholar, D.A.V. (PG)  
College, Bulandshahr, India

#### Corresponding Author:

Shivam Chauhan

#### DOI:

<https://doi.org/10.70096/tssr.260402107>

#### Abstract

Do voters reward governments for aggregate economic growth? Using satellite-derived night-time light (NTL) radiance as a proxy for constituency-level economic activity across all 543 Indian parliamentary constituencies and three Lok Sabha elections (2014, 2019, 2024), this paper tests whether NTL growth under a decade of single-party majority predicts electoral outcomes for the incumbent. Across two government terms, winner and BJP-specific vote-share models, the NTL coefficient is statistically and economically indistinguishable from zero throughout. Mean reversion in vote shares is the dominant structural force in both cycles. The null testifies that NTL captured diffuse, non-attributable sociotropic growth have no effect on the voting behaviour.

**Keywords:** *night-time lights; India; economic voting; pocketbook vs sociotropic voting; welfare politics; electoral accountability*

### Introduction

The fundamental question of democratic accountability is whether voters reward governments for economic performances. If they do, elections create structural incentives for better governance. If not, they become contests of identity, patronage, and mobilisation. Understanding which mechanism prevails in large developing democracies is among the most consequential questions in comparative political economy.

India between May 2014 and June 2024 offers an unusually clean test. A single coalition governed the central government across two full terms, creating clear attribution conditions rare in parliamentary systems. Night-time light (NTL) radiance from VIIRS satellite imagery provides an objective, manipulation-resistant, consistently measured proxy for constituency-level economic activity across all 543 parliamentary constituencies. Three Lok Sabha elections bracket two complete government terms.

The NTL growth in the 2014–2018 window covers BJP's first term and is measured one year before the May 2019 election; the 2019–2023 window covers BJP's second term and is measured one year before the June 2024 election.

The central empirical question is whether NTL-measured aggregate economic activity growth at the constituency level predicts vote-share gains for the incumbent, controlling for prior vote shares, baseline development, and state fixed effects. The answer, across every specification estimated, is no.

The paper makes three contributions. First, it provides the first comprehensive constituency-level test of aggregate NTL growth effects across three elections and two full government terms, filling a gap left by prior work that examined either individual welfare programmes or state-level patterns. Second, it disentangles the NTL signal into constituencies where growth reflects electrification infrastructure provision versus genuine economic activity, showing the null holds in both. Third, it interprets the null through the pocketbook versus sociotropic distinction: NTL captures diffuse, non-attributable growth; the BJP's Direct Benefit Transfer (DBT) architecture delivered named, personally experienced, pocketbook-level transfers that are electorally traceable in ways ambient luminosity is not.

### Theoretical Framework

#### Economic Voting: Pocketbook and Sociotropic Channels

Classical retrospective voting theory holds that voters assess government performance and reward or punish accordingly (Key, 1966). Two channels are distinguished in the literature. Pocketbook voting (Fiorina 1981) concerns individual economic experience on whether the voter personally is better off. Sociotropic voting (Kinder and Kiewiet 1981) concerns aggregate

economic conditions on whether the economy as a whole is performing well. These channels differ in the information they require: pocketbook voting is activated by direct personal experience, sociotropic voting by perceived aggregate conditions that voters must (a) accurately observe and (b) correctly attribute to the government in power.

NTL radiance is a sociotropic measure. It captures ambient luminosity growth across a constituency—a signal that benefits all residents regardless of vote choice and that individual voters neither directly observe nor attribute to a specific government. The DBT architecture BJP constructed operates on an entirely different logic: LPG cylinders bearing the Prime Minister's photograph, cash installments credited to named Jan Dhan accounts, housing units with official plaques—these are pocketbook transfers. The recipient perceives them as personal, experiences them directly, and attributes them explicitly to the government that arranged them.

Powell and Whitten (1993) show that economic voting is stronger when attribution is clear. Achen and Bartels (2016) go further, arguing that most apparent economic voting reflects "blind retrospection"—voters reacting to personally salient events rather than systematically evaluating policy performance. The DBT architecture is the structural opposite of blind retrospection: it produces sighted, named, personally experienced retrospection. NTL-visible economic growth, by contrast, is precisely the kind of diffuse, unattributed signal that Achen and Bartels argue voters cannot reliably connect to government action.

### **NTL as an Economic Proxy and the Saubhagya**

Henderson, Storeygard, and Weil (2012) validated satellite-derived NTL radiance as a proxy for GDP growth. Chen and Nordhaus (2011) confirmed its utility at sub-national scales. Asher and Novosad (2017) demonstrated validity at the Indian local level, with correlations to survey-based consumption measures and responsiveness to political cycles.

A critical limitation for India during 2014–2022 is that NTL growth conflates two economically distinct processes: productive economic activity (manufacturing, services, commercial density) and one-time electrification infrastructure provision via the Saubhagya programme (26 million rural household connections, 2017–2019) and DDUGJY feeder separation. A village gaining household electricity connections appears dramatically brighter in satellite imagery even if productive economic activity has not changed. This paper directly addresses this confound in Section 4.2, splitting constituencies by their 2013 baseline luminosity to separate catch-up electrification from ongoing economic growth. The null holds in both groups.

### **India as a Critical Case**

India during 2014–2024 combines ideal conditions for detecting economic voting alongside structural barriers. The ideal conditions are genuine: single-coalition central rule for a decade, an unusually centralising prime minister effective at credit-claiming, and 543 constituencies providing statistical power uncommon in cross-national studies. The structural barriers are equally real: over 90% informal employment (ILO, 2018), federal attribution complexity where state governments implement locally felt policies, historically identity-based electoral mobilisation (Chandra, 2004; Chibber & Verma, 2018), and a government that deliberately replaced diffuse public goods with individually targeted private transfers.

Prior micro-level work using National Election Study data found that Ujjwala LPG beneficiaries were 7.5 percentage points more likely to vote BJP than comparable non-recipients; Jan Dhan account holders 5.2 points more likely; PM Awas beneficiaries 8.3 points more likely—and recipients were significantly more likely to credit the central government specifically (Deshpande et al., 2019). Carnegie Endowment analysis confirmed these patterns (Singh, 2024). These are pocketbook effects from named transfers. The present paper's question is whether the sociotropic channel—aggregate NTL-visible growth—operates in parallel. It does not.

### **Data and Empirical Strategy**

#### **Night-Time Light Data**

VIIRS Day-Night Band Black Marble Annual Composites (NASA VNP46A4 v2.1 for 2013–2021, v2.2 for 2022 onwards). Mean radiance in nanowatts per square centimetre per steradian (nW/cm<sup>2</sup>/sr) extracted via Google Earth Engine for all 543 parliamentary constituency polygons. Two treatment variables are constructed using a symmetric pre-election-year stopping rule:

**NTL growth, 1st term:**  $(NTL_{2018} - NTL_{2024}) / NTL_{2014} \times 100$ . Window 2014–2018—one year before the May 2019 election. Mean = +53.6%, SD = 43.4%.

**NTL growth, 2nd term:**  $(NTL_{2023} - NTL_{2019}) / NTL_{2019} \times 100$ . Window 2019–2023—one year before the June 2024 election. Mean = +35.8%, SD = 18.6%. The higher SD relative to the first term reflects greater cross-constituency variation in second-term growth patterns.

#### **Election Data**

2014 and 2019: TCPD Lok Dhaba database (Trivedi Centre for Political Data, Ashoka University, 2024). 2024: Election Commission of India official results (ECI, 2024). All 543 constituencies are matched across all three sources (100% match rate); 27 constituency-level naming discrepancies resolved via lookup mapping. Surat 2024 is excluded from 2019–24 winner models (BJP won uncontested; no valid votes cast), giving  $n = 540$  for winner models and  $n = 435$  for BJP-contested models in the 2nd cycle.

Two outcome variables are used. Winner vote-share change ( $\Delta VS_t^{win}$ ) is the winning candidate's vote share in election  $t$  minus their predecessor's share in  $t - 1$ , regardless of party—the standard measure in the economic voting literature. BJP vote-share change ( $\Delta VS^{BJP}$ ) is BJP's specific vote share change, zero if BJP did not contest, measuring the party's own electoral trajectory.

**Estimation Strategy**

A single specification is estimated separately for each election cycle and each outcome:

$$\Delta VS_i = \alpha + \beta_1 \cdot NTL\_growth_i + \beta_2 \cdot \log(NTL\_baseline_i) + \beta_3 \cdot VS\_prior_i + \gamma_s + \varepsilon_i$$

OLS with HC3 heteroskedasticity-robust standard errors (MacKinnon & White, 1985).  $\gamma_s$  are 35 state and union territory fixed effects. The coefficient of interest is  $\beta_1$ . Classical economic voting predicts  $\beta_1 > 0$  and substantively meaningful.  $VS\_prior$  controls for mean reversion: extreme starting positions structurally regress toward the mean, and this must be disentangled from economic performance effects.

**Results**

**Main Regressions**

Table 1 presents descriptive statistics. Table 2 reports the main regression results across four models. The coefficient on NTL growth is statistically and economically zero in every model.

Variable	n	Mean	SD	Min	Median	Max	Notes
Outcome variables							
Winner $\Delta VS$ 2014–19 (pp)	542	5.38	8	–21.2	5.4	26.6	Winner dep. var., 2019
Winner $\Delta VS$ 2019–24 (pp)	540	–2.17	7.25	–30.4	–2.3	30.2	Surat excl. (uncontested)
BJP $\Delta VS$ 2014–19 (pp)	428	5.38	14.04	–53.7	4	52.2	BJP-contested only
BJP $\Delta VS$ 2019–24 (pp)	435	–0.61	13.29	–60.6	–0.97	56.4	BJP-contested only
Treatment variables							
NTL growth, 1st term 2014–2018 (%)	543	53.6	43.4	–44.7	47.1	289.6	Window: 2014–2018
NTL growth, 2nd term 2019–2023 (%)	543	35.8	18.6	–10.0	35.2	97.7	Window: 2019–2023
Controls							
$\log(1 + NTL\ baseline)$	543	—	—	—	—	—	Baseline development control
Prior vote share (%)	543	—	—	—	—	—	Mean reversion control
State fixed effects (35)	—	—	—	—	—	—	Within-state identification

Table 1: Descriptive statistics. pp = percentage points. NTL growth windows stop one year before the election in each cycle (2014–2018 for 2019; 2019–2023 for 2024), ensuring methodological symmetry. BJP  $\Delta VS$  uses contested constituencies only. Surat 2024 excluded (uncontested).

Variable	2014–2019 cycle				2019–2024 cycle			
	(1) Winner $\Delta VS$		(2) BJP $\Delta VS$		(3) Winner $\Delta VS$		(4) BJP $\Delta VS$	
	$\beta$	SE	$\beta$	SE	$\beta$	SE	$\beta$	SE
NTL growth KEY TEST	0.0043	0.0114	0.0025	0.0356	–0.0236	0.0253	–0.0398	0.041
p-value (n.s. throughout)	0.706	—	0.944	—	0.351	—	0.333	—
log NTL baseline	1.234	0.445	–1.320	0.983	0.919	0.432	1.129	0.668

<i>p</i> -value	0.006**	—	0.180 n.s.	—	0.034*	—	0.092 n.s.	—
Prior vote share DOMINANT	-0.605	0.043	-0.127	0.083	-0.587	0.048	-0.145	0.052
<i>p</i> -value	<0.001***	—	0.128 n.s.	—	<0.001***	—	0.005**	—
State FE / n	35/542	—	35/428	—	35/540	—	35/435	—
R <sup>2</sup> (overall)	0.557	—	0.446	—	0.532	—	0.44	—
Bivariate Pearson <i>r</i>	+0.126**	—	-0.124**	—	-0.037 n.s.	—	+0.078 n.s.	—
Bivariate Spearman $\rho$	+0.054 n.s.	—	+0.009 n.s.	—	+0.005 n.s.	—	+0.155***	—

Table 2: Main regression results. OLS + State FE (35 dummies) + HC3 robust SEs. \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , n.s. = not significant. NTL windows: 2014–2018 (1st cycle); 2019–2023 (2nd cycle). Models (2) and (4) use BJP-contested constituencies only. The bivariate Pearson  $r = +0.126^{**}$  in model (1) collapses to  $\beta = +0.0043$  ( $p = 0.706$ ) once controls enter; Spearman  $\rho = +0.054$  n.s. confirms the bivariate signal is outlier-driven.

Figure 1. Binscatter Plots: NTL Growth vs Electoral Outcomes (40 equal-size bins,  $\pm 1$  SE). NTL windows: 2014–2018 for 2019 election; 2019–2023 for 2024 election | Panels A-D: key test. Panels E-F: mean reversion benchmark.

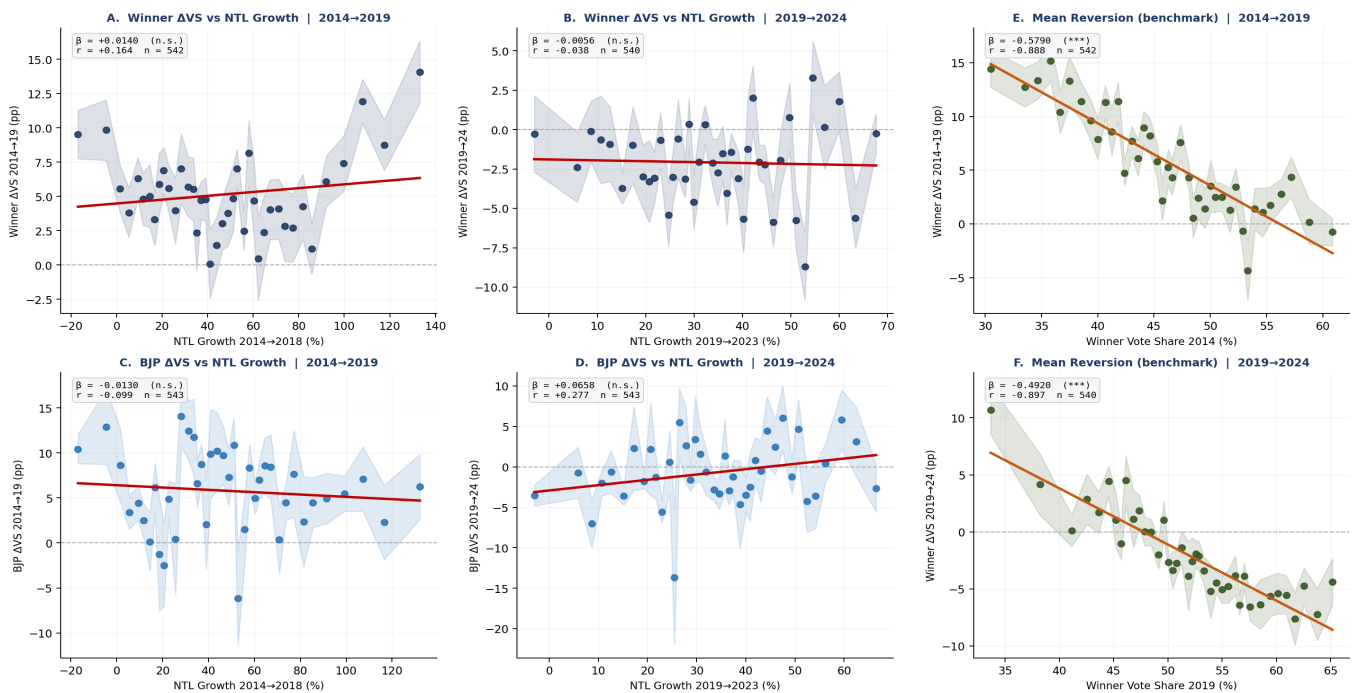


Figure 1. Binscatter plots (40 equal-size bins,  $\pm 1$  SE shading). Panels A–D: NTL growth (2014–2018 and 2019–2023 respectively) vs winner and BJP vote-share changes—flat slopes throughout. Panels E–F: prior vote share vs  $\Delta$ VS, shown as mean-reversion benchmark—strong negative slopes.

### NTL Signal Decomposition: Does the Saubhagya Confound Drive the Null?

A potential objection is that the null reflects the Saubhagya programme rather than the absence of economic voting: NTL growth in many constituencies captures electrification infrastructure provision, not productive activity, so voters may correctly perceive no meaningful economic improvement. This confound is addressed directly by splitting constituencies into three groups by their 2013 baseline NTL radiance: electrification catch-up ( $NTL_{2013} < 0.5$  nW/cm<sup>2</sup>/sr,  $n = 176$ ), transition ( $0.5–2.0$ ,  $n = 285$ ), and stable lights ( $NTL_{2013} > 2.0$ ,  $n = 82$ ), where growth represents genuine economic activity. If the Saubhagya confound is responsible for the null, the stable-lights group should show a positive  $\beta_1$ . It does not.

NTL Group (baseline 2013)	$\beta$ Winner 14–19	p	$\beta$ Winner 19–24	p	n	NTL growth (mean)	Interpretation

Catch-up (NTL <sub>2013</sub> < 0.5 nW) n=176	0.024	0.459 n.s.	-0.030	0.501 n.s.	176 / 42	2.12230216	NTL ≈ Saubhagya; null holds
Transition (0.5–2.0 nW) n=285	-0.012	0.485 n.s.	-0.014	0.609 n.s.	285 / 399	1.21311475	Mixed signal; null holds
Stable lights (NTL <sub>2013</sub> > 2.0 nW) n=82	0.03	0.711 n.s.	0.046	0.545 n.s.	82 / 102	0.3633218	Economic activity; null holds

Table 3: NTL signal decomposition.  $\beta$  on NTL growth within each group, OLS + State FE + HC3. n column shows group sizes for 1st cycle / 2nd cycle (groups reclassified using NTL\_2019 for the 2nd cycle). The critical test is the Stable Lights row: even where NTL growth reflects genuine economic activity, voters do not reward the incumbent. The Saubhagya confound does not drive the null.

Figure 2. NTL Signal Decomposition: Electrification Catch-up vs Stable Lights  
NTL window 2014–2018 (row 1) and 2019–2023 (row 2) | Null holds in all six sub-groups.

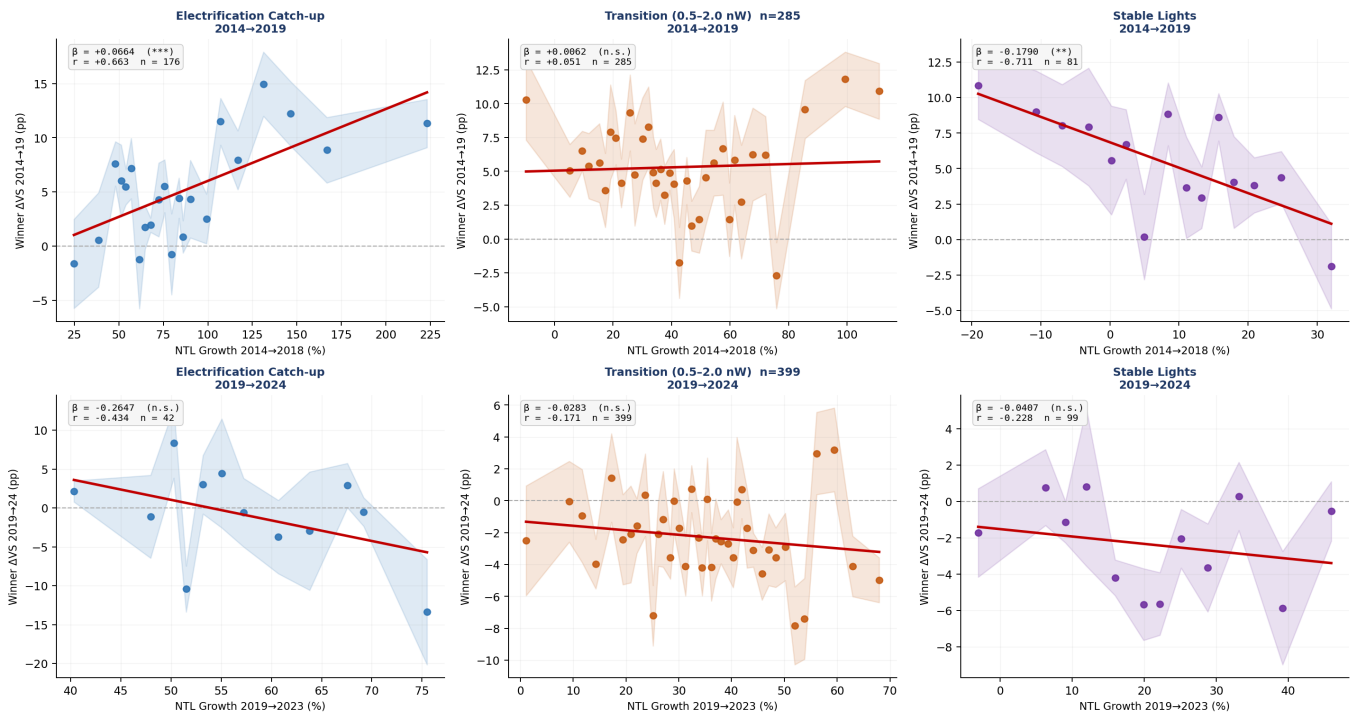


Figure 2. NTL decomposition binscatter plots within each constituency type. Row 1: 2014–19 (NTL 2014–2018). Row 2: 2019–24 (NTL 2019–2023). All six panels show flat slopes. The stable-lights group (right column) is the purest test of economic voting.

## Discussion

### Why the 2019 Bivariate Signal Disappears

The 2019 winner model shows a bivariate Pearson  $r = +0.126$  ( $p < 0.01$ ), which might appear to support economic voting. Three features of the data refute this. First, the same cycle's BJP model gives  $r = -0.124$  ( $p < 0.01$ )—an opposite sign. A genuine economic voting signal would produce positive correlations for both. Second, the Spearman rank correlation is  $+0.054$  and  $+0.009$  respectively—both statistically zero—indicating the Pearson signal is driven by outliers rather than a monotonic relationship. Third, once  $VS_{2014}$  is controlled,  $\beta_1 = +0.0043$  ( $p = 0.706$ ).

The spurious bivariate correlation traces to BJP's 2014 wave. It concentrated in low-NTL rural constituencies of Uttar Pradesh, Bihar, Rajasthan, and Madhya Pradesh—precisely the areas with the lowest baseline luminosity and therefore the most room for both electrification catch-up (generating NTL growth) and electoral consolidation from narrow 2014 wins (generating vote-share gains in 2019). Both processes shared the same starting condition—low 2014 baseline—not any causal relationship between luminosity growth and electoral reward. Controlling for  $VS_{2014}$  severs this spurious link.

### The Attribution Gap

The null is not a puzzle once the sociotropic–pocketbook distinction is applied. NTL radiance captures non-excludable, diffuse, aggregate growth. A constituency that has added street lights and electrified homes appears brighter in satellite imagery; this benefit accrues to every resident regardless of vote choice, and no individual voter perceives "my constituency's NTL grew 54% during 2014–2018" as a concrete, personally experienced fact.

The BJP government built its electoral strategy on the opposite logic. The Pradhan Mantri Ujjwala Yojana delivered LPG cylinders bearing the Prime Minister's photograph. The PM-Kisan scheme transferred ₹2,000 directly into named Jan Dhan accounts three times per year. The PM Awas Gramin programme built housing units with official plaques. These are excludable transfers: they can be targeted to specific households, and the recipient knows exactly who arranged them. Kitschelt and Wilkinson (2007) argue that private good delivery is more electorally efficient than public goods precisely because it creates observable, traceable credit-claiming links. NTL captures precisely the class of non-excludable goods that are electorally inefficient.

The micro-level evidence corroborates this. Deshpande, Tillin, and Kailash (2019) found Ujjwala recipients were 7.5 percentage points more likely to vote BJP than comparable non-recipients, Jan Dhan holders 5.2 points, PM Awas beneficiaries 8.3 points. Carnegie Endowment analysis confirmed these effects were strongest among households that had previously supported opposition parties: DBT programmes shifted votes, they did not merely mobilise existing supporters (Shikhar Singh, 2024). These pocketbook effects explain 2019 consolidation; NTL growth does not.

### Mean Reversion as the Structural Dominant

The prior vote-share coefficient ( $\beta_3 \approx -0.60$  in winner models,  $p < 0.001$  throughout) dwarfs the NTL coefficient in both magnitude and significance. This is mean reversion: extreme starting positions structurally regress toward the mean in subsequent elections, irrespective of economic performance. In 2019, mean reversion worked for BJP as narrow 2014 wave-entry seats consolidated. In 2024, it reversed: BJP's inflated 2019 position of 303 seats, many won by large margins in semi-urban territories outside traditional strongholds, created a high base from which regression was structurally predictable, independent of any economic performance variable.

### The 2024 Election: Welfare Normalisation and Distributional Grievances

The 2024 result—winner vote shares declining 2.17 percentage points on average, BJP losing 63 seats nationally—is fully consistent with the null on NTL. The decline is not explained by slower NTL growth: Maharashtra and Karnataka, which lost 14 and 8 BJP seats respectively, had among the highest second-term NTL growth nationally (+24% range). Rajasthan lost 10 BJP seats with similarly high NTL growth. Odisha gained 12 seats with the highest NTL growth in the sample—but this reflects the BJD collapse, not economic reward.

State	Seats 2019	Seats 2024	Change	Winner $\Delta$ VS	NTL growth 2019–2023	Political driver (independent of NTL)
Uttar Pradesh	62	33	–29	–4.59pp	21.80%	<i>INDIA alliance coordination; SP-Congress seat-sharing reduced vote splitting</i>
Maharashtra	23	9	–14	–3.08pp	31.40%	<i>Maratha quota agitation; MVA caste coalition; high NTL growth, large seat loss</i>
Karnataka	25	17	–8	–0.93pp	29.30%	<i>Lingayat-Vokkaliga JDS+Congress coordination; high NTL growth, seat loss</i>
Rajasthan	24	14	–10	–6.72pp	24.60%	<i>Agricultural distress; 2023 state election loss momentum; rural anti-incumbency</i>
Odisha	8	20	12	+1.75pp	51.20%	<i>BJD collapse; BJP-BJD split; anti-incumbency against 24-yr BJD state govt</i>
Gujarat	26	26	0	–1.12pp	22.40%	<i>BJP traditional stronghold; held seats despite VS decline</i>

*Table 4: State-level 2024 BJP seat changes with NTL growth (2019–2023 window). The two states with the highest NTL growth (Odisha, Maharashtra) had opposite electoral outcomes. NTL growth predicts neither the direction nor magnitude of 2024 seat changes. NTL values are constituency-level means aggregated to state level for illustration.*

What explains 2024 independently of NTL? Two channels. First, welfare entitlement normalisation: a household that received an Ujjwala LPG connection in 2016 has used the cylinder for eight years. It is no longer a novel personal gift but an ordinary consumption item whose marginal electoral value has depreciated toward zero. Second, distributional grievances: CMIE data showed unemployment rates for 20–24 year-olds reaching 44% in urban areas during 2022–2023 (CMIE, 2023); food staple

inflation exceeded 8–10% annually in 2022–2023 (RBI, 2023). These are experienced through wages, bills, and job searches—none of which are captured in satellite luminosity.

The evidence is consistent with semi-urban constituencies (NTL 1–5 nW/cm<sup>2</sup>/sr) showing steeper BJP declines in 2024 than rural constituencies (NTL < 1). Semi-urban areas are where youth unemployment-aspiration mismatch is sharpest and where inflation is most salient as a monetised consumption item. This pattern is not derived from NTL growth—semi-urban constituencies did not have systematically lower NTL growth—but from the structure of distributional grievances that NTL is constitutionally unable to measure.

### Conclusion

This paper has tested whether Indian voters rewarded the BJP-led government for constituency-level aggregate economic growth, measured by satellite night-time light radiance, across three Lok Sabha elections and two full government terms. The answer is clear: NTL-visible aggregate growth has no independent electoral effect in any specification. The null survives the separation of electrification catch-up from genuine economic activity, and it survives across winner and BJP-specific vote-share models in both cycles.

NTL is a sociotropic, non-excludable, diffuse signal. India's accountability during 2014–2019 operated through pocketbook, excludable, personally named welfare transfers. These are not substitutes for each other in the voter's information set; they are qualitatively different inputs that activate different accountability channels. Micro-level evidence confirms the pocketbook channel was working—welfare recipients voted BJP at significantly higher rates and credited the centre explicitly. The sociotropic channel, for which NTL is the appropriate proxy, shows no electoral trace.

The 2024 outcome confirms the logic. BJP lost 63 seats nationally despite continued positive NTL growth in most states. The losses are explained by welfare normalisation and distributional grievances that are independent of, and orthogonal to, NTL-measured aggregate growth. Satellites cannot measure individual grievances of votes. Electoral accountability in 2024 responded to what voters experienced in their daily lives—exactly what sociotropic models predict voters will fail to systematically evaluate and attribute.

For democratic theory more broadly: if large developing democracies hold governments accountable primarily through pocketbook welfare transfers rather than aggregate performance, the long-run governance consequences are deeper. Governments will prioritize the unsustainable welfare transfers over the sustainable aggregate economic activities.

**Acknowledgment:** No

**Author's Contribution:** Shivam Chauhan: Data Collection, Literature Review, Methodology, Analysis, Drafting, Referencing

**Funding:** No

**Declaration:** The author has given consent for the publication.

**Competing Interest:** No

### References

1. Achen, C. H., & Bartels, L. M. (2016). *Democracy for realists*. Princeton University Press.
2. Asher, S., & Novosad, P. (2017). Politics and local economic growth: Evidence from India. *American Economic Journal: Applied Economics*, 9(1), 229–273.
3. Centre for Monitoring Indian Economy. (2023). *Unemployment rate in India*. <https://cmie.com>
4. Chandra, K. (2004). *Why ethnic parties succeed*. Cambridge University Press.
5. Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21), 8589–8594.
6. Chhibber, P., & Verma, R. (2018). *Ideology and identity: The changing party systems of India*. Oxford University Press.
7. Deshpande, R., Tillin, L., & Kailash, K. K. (2019). The BJP's welfare schemes: Did they make a difference in the 2019 elections? *Studies in Indian Politics*, 7(2), 219–233.
8. Election Commission of India. (2024). *General election to Lok Sabha 2024: Results*. <https://results.eci.gov.in>
9. Fiorina, M. P. (1981). *Retrospective voting in American national elections*. Yale University Press.
10. Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2), 994–1028.
11. International Labour Organization. (2018). *Women and men in the informal economy* (3rd ed.).
12. Key, V. O. (1966). *The responsible electorate*. Harvard University Press.
13. Kinder, D. R., & Kiewiet, D. R. (1981). Sociotropic politics: The American case. *British Journal of Political Science*, 11(2), 129–161.
14. Kitschelt, H., & Wilkinson, S. I. (Eds.). (2007). *Patrons, clients, and policies*. Cambridge University Press.
15. MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, 29(3), 305–325.

16. Powell, G. B., & Whitten, G. D. (1993). A cross-national analysis of economic voting. *American Journal of Political Science*, 37(2), 391–414.
17. Reserve Bank of India. (2023). *Consumer price index: Food and beverages*. <https://rbi.org.in>
18. Singh, S. (2024). *When does welfare win votes in India?* <https://carnegieendowment.org>
19. Trivedi Centre for Political Data. (2024). *Lok Dhaba*. Ashoka University. <https://lokhaba.ashoka.edu.in>

**Publisher's Note**

*The Social Science Review A Multidisciplinary Journal* remains neutral with regard to jurisdictional claims in published data, map and institutional affiliations.

**©The Author(s) 2026. Open Access.**

This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>