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The Enclave Penalty: Tribes, Caste, and Electricity Reliability in India

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Abstract

India has achieved near-universal electrification, yet large inequalities persist in the reliability of the electricity supply. Combining high-resolution satellite-based measures of electricity reliability — defined as the share of nights with detectable illumination — with village-level census data, this paper shows that reliability remains systematically unequal across social groups. While Scheduled Caste villages largely track district-level reliability, Scheduled Tribe (ST) villages face a pronounced enclave penalty. Homogeneous ST enclaves (ST population ≥ 90%) exhibit 10.7 percentage points fewer illuminated nights than otherwise comparable villages within-district with low ST shares. We further identify a mobility trap: homogeneous ST enclaves are about 16.6 (16.0) percentage points more likely to remain energy poor in 2012 (2019) and 11.7 percentage points less likely to escape energy poverty between 2012 and 2019. These findings suggest that as access becomes universal, infrastructure exclusion increasingly operates through a less visible rationing of service quality in socially homogeneous tribal settlements.

JEL classification

O13, O18, Q41, R12

Keywords

electricity reliability, energy poverty, caste, tribes, India, night-time lights

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1 Introduction

Over the past decade, India has made unprecedented progress toward universal electricity access. Flagship initiatives such as the Saubhagya scheme led the Government of India to declare near-complete household electrification by 2018, marking a historic expansion of grid infrastructure, progress that aligns with Sustainable Development Goal 7's 2030 objective of universal access to affordable and reliable energy services. Official statistics indicate that the vast majority of Indian villages are now connected to the national grid (Ministry of Power, 2026), strengthening a narrative of convergence in access to critical public goods (Banerjee and Somanathan, 2007). However, access to electricity does not guarantee its effective use. A growing literature emphasizes that while poles and wires may have reached most settlements, the reliability of electricity supply—measured in hours of availability and consistency over time—remains deeply uneven. Power cuts, load shedding, and voltage fluctuations continue to constrain household welfare (Burgess et al., 2020) and local economic activity (Allcott et al., 2016), particularly in rural areas.

From an economic perspective, reliability of electricity is a different outcome from access: it is a flow of service that depends on real-time balancing, operational decisions, and institutional incentives rather than solely on the presence of physical infrastructure (Borenstein et al., 2023). Survey-based studies of energy poverty in India demonstrate that income growth alone does not eliminate energy deprivation, highlighting the importance of non-monetary dimensions such as reliability and quality of service (Sadath and Acharya, 2017; Gupta et al., 2020).

Recent experimental evidence from Kenya suggests that grid expansion alone may generate limited economic returns due to low demand and low electricity usage, even when connections are available (Lee et al., 2020). Similarly, using administrative data from India's earlier RGGVY wave, Burlig and Preonas (2024) find that despite massive infrastructure expansion, electrification had zero detectable effect on local economic activity, largely due to unreliable and limited electricity supply. However, while these demand-side constraints are well documented, they leave unresolved whether electricity reliability is shaped solely by usage and affordability or whether it also reflects supply-side discretion in service provision.

In this paper, we study whether this quality gap in electricity provision is systematically structured along social lines—specifically castes and tribes. India's caste system is a hereditary social hierarchy that has structured economic and social life for centuries. The Indian Constitution identifies two historically marginalized groups for affirmative action: Scheduled Castes (SC), historically known as untouchables or Dalits, who occupy the lowest rung of the ritual hierarchy and have faced systematic social discrimination, economic exclusion, and residential segregation; and Scheduled Tribes (ST), also known as Adivasis, who are indigenous communities typically residing outside the caste hierarchy in geographically remote, forested, or hilly regions. Together, these groups constitute approximately 25% of India's population—about 201.4 million SC and 104.3 million ST as of the 2011 Census. In rural India, SCs constitute 18.5% and STs 11.3% of the rural population (roughly 154 million rural SC and 94 million rural ST residents). While both groups are targets of constitutional protections, reservations in public employment and legislatures, and targeted welfare programs, their spatial organization differs fundamentally, with distinct implications for how public goods exclusion operates.

This distinction is central to our analysis: while SC exclusion is often driven by social discrimination within integrated economies, ST exclusion is characteristically driven by social homogeneity, which facilitates exclusion via group-level targeting. Building on foundational work linking night-time lights to economic activity (Henderson et al., 2012), we use the High-Resolution Electricity Access (HREA) dataset derived from VIIRS-DNB (Visible Infrared Imaging Radiometer Suite Day/Night Band) sensors, which improves substantially on earlier DMSP-OLS (Defense Meteorological Satellite Program Operational Linescan System) measures by offering finer spatial resolution and reduced light blooming (Min et al., 2024). HREA constructs probabilistic measures of persistent night-time illumination in approximately 500 m × 500 m grid cells, capturing the reliability—defined as the proportion of nights illuminated within a year—rather than the mere presence of grid infrastructure. We spatially aggregate these grid-level measures to village boundaries using the Census 2011 village shape file provided by Socioeconomic High-Resolution Rural–Urban Geographic (SHRUG) (Asher et al., 2021). We merge this with comprehensive village-level census data and examine whether villages with higher shares of SC and ST populations experience systematically lower electricity reliability, even after near-universal grid expansion. Crucially, all specifications include district fixed effects and control for detailed topographic features, settlement density, remoteness, and indicators of existing state presence — ensuring that estimated disparities reflect social exclusion rather than the physical costs of reaching rugged or remote settlements. By focusing on reliability as a flow of service rather than infrastructure as a stock, we shift the analysis of energy poverty from whether electricity exists to whether—and for how many hours—it is actually supplied. Finally, we examine how these disparities in reliability contribute to persistent poverty traps and unequal rates of upward mobility across villages.

Our analysis builds on a political economy literature that views public goods provision in developing democracies as inherently discretionary. Golden and Min (2013) argue that politicians strategically allocate public goods to maximize electoral returns, favoring goods that are visible, attributable, and reversible. Electricity is particularly well suited to such targeting. Unlike roads or schools, electricity is a flow variable: supply can be increased or curtailed in real time. Using satellite night-time lights, Min and Golden (2014) show that electricity provision in India exhibits pronounced political cycles. Crucially, Baskaran et al. (2015) demonstrate that this manipulation can be geographically targeted: state governments successfully direct power to specific constituencies during special elections, proving that the grid can be managed with high spatial precision. More recent work documents how political incentives degrade grid quality. When politicians enable power theft for favored constituents (Mahadevan, 2024) or reinforce an entitlement norm that weakens cost recovery—through subsidies, nonpayment, and illegal connections (Burgess et al., 2020), utilities face chronic revenue shortfalls. Confronted with these deficits, distribution companies resort to non-price rationing by limiting hours and quality of supply. We argue that the burden of this rationing falls disproportionately on socially homogeneous tribal enclaves, which lack the political leverage to demand reliable service. Crucially, the discretion inherent in managing electricity flows creates an opening for the kind of subtle, supply-side discrimination documented experimentally by Hanna and Linden (2012). In their study, teachers systematically assigned lower grades to exams attributed to low-caste students, demonstrating that when bureaucratic processes allow for subjectivity, administrative outcomes can be biased against marginalized groups.

We extend this political economy framework beyond electoral cycles to examine whether electricity is also rationed socially. If electricity can be targeted politically, can it also be rationed along caste lines? This question connects both to foundational theories linking social fragmentation to the under-provision of public goods (Alesina et al., 1999), and to evidence that the identity of political representatives shapes resource allocation (Pande, 2003). In the Indian context, Banerjee and Somanathan (2007) document that constituencies with higher SC populations historically received fewer public goods, but they also show that political mobilization during the 1980s and 1990s led to substantial convergence in access to static infrastructure such as schools and drinking water. However, whether this convergence extends to all public goods and services remains an open question. Recent evidence presents a more nuanced picture: while some basic infrastructure has equalized, disparities persist for higher-order or more complex services. For example, Bailwal and Paul (2021) find that while primary school provision has largely converged across caste groups, villages with higher SC/ST populations continue to have significantly lower probabilities of receiving secondary schools, suggesting that supply-side disadvantage may persist for more advanced public goods.

Our main findings are threefold. First, using Census 2011 administrative data, we show that SC–majority villages within a district do not differ from comparable villages in either electricity access or reported hours of supply, whereas ST–majority villages exhibit significantly lower access rates and fewer hours of electricity supply—a gap that persists even when comparing villages with similar terrain, state-capacity, and distance to urban centers within the same district. Second, when we examine satellite-based measures of electricity reliability in 2012, the disadvantage faced by ST-majority villages is substantially larger than what is observed in administrative access data—nearly twice as large in magnitude—suggesting that official electrification statistics substantially understate the extent of service deprivation in tribal villages. This reliability penalty widens marginally in 2019: despite near-universal reported grid access, ST-majority villages remain significantly less likely to be reliably illuminated at night. Third, using alternative reliability-based thresholds to define energy poverty, we find that ST-majority villages are significantly more likely to be energy poor in both 2012 and 2019, and exhibit a pronounced mobility trap, being approximately 11.7 percentage points less likely to escape energy poverty over this period compared to similarly deprived non-tribal villages.

These findings complicate the prevailing convergence narrative in India. While earlier work documents catch-up in access to static infrastructure such as schools and roads (Banerjee and Somanathan, 2007), and the energy poverty literature demonstrates that income growth alone does not eliminate deprivation (Sadath and Acharya, 2017; Gupta et al., 2020), neither approach is well suited to detecting supply-side disparities in service quality. By leveraging objective satellite-based measures — which reveal that official electrification statistics often capture infrastructure presence rather than effective use (Dugoua et al., 2022; Min et al., 2024) — we uncover a systematic reliability penalty invisible to administrative records.[1]

More broadly, our findings imply that electrification alone is insufficient to eliminate inequality in energy welfare. As governments move from expanding access to improving quality, the distributional consequences of infrastructure provision increasingly hinge on

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[1] Min et al. (2024) illustrate this discrepancy using the case of Dherhi, a village in Uttar Pradesh that was officially electrified in 2007 but showed no stable night-time lights until 2017.

who receives reliable service rather than who is formally connected. Policies and monitoring frameworks that focus exclusively on connections risk obscuring persistent forms of exclusion concentrated in spatially segregated tribal regions. Ensuring equitable energy welfare therefore requires explicit attention to reliability—particularly in communities where service shortfalls are less visible but more enduring.

We proceed by first documenting the spatial segregation of SC and ST, then comparing administrative and satellite-based measures of electricity reliability, before examining dynamics, energy poverty, and mobility traps.

2 Data and Descriptive Statistics

2.1 Data Sources

Our analysis is conducted at the harmonized village level, utilizing the standardized village identifiers and polygon geometries provided by the Socioeconomic High-Resolution Rural–Urban Geographic Dataset (SHRUG). SHRUG reconciles Census villages across time and assigns each village a unique identifier (`shrid`), which serves as the primary unit of analysis throughout the paper (Asher and Novosad, 2020; Asher et al., 2021). All administrative and satellite-based variables are mapped to this common spatial unit.

The core administrative data comes from the Census of India 2011 Village Directory (VD). The VD provides comprehensive information on village demographics, including the total population and the SC and ST populations. It also reports official indicators of electricity access for domestic use and, for villages classified as electrified, administrative measures of average daily electricity supply during the summer/winter months. We complement these administrative records with satellite-derived measures of electricity provision from the High-Resolution Electricity Access (HREA) dataset. HREA applies probabilistic methods to VIIRS night-time light imagery to capture de facto electricity reliability rather than nominal access (Min et al., 2024). Relative to earlier night-light products, HREA offers substantially finer spatial resolution and probabilistic illumination measures that are less sensitive to saturation and light blooming. This distinction is critical for our analysis; as Gibson et al. (2021) demonstrate, older DMSP data suffer from severe blurring, top-coding, and lack of calibration, which generate mean-reverting measurement error and substantially understate spatial inequality—especially at fine spatial scales and in low-density rural areas. VIIRS data are radiometrically calibrated and perform markedly better in detecting spatial variation in lighting intensity. Given our focus on detecting exclusionary pockets (enclaves) within districts, the superior dynamic range and spatial precision of VIIRS are essential.

Finally, to account for physical settlement density independent of electrification, we incorporate village-level built-up surface density from the Global Human Settlement Layer (GHSL). GHSL is measured at 3-arc-second resolution (approximately 100 meters at the equator) in the WGS84 geographic coordinate system and provides a control for the extent of constructed area within village boundaries (Pesaresi et al., 2024). We further control for topography using data from the NASA Shuttle Radar Topography Mission (SRTM) (Farr and Kobrick, 2000). We utilize village-level mean elevation and the Terrain Ruggedness Index (TRI), which measures the variation in elevation within the village polygon, as provided by the SHRUG open data platform (Asher et al., 2021).

2.1.1 Key Outcomes

We study two classes of electricity outcomes, allowing us to contrast official measures of government provision with de facto service delivery.

1. Administrative Access and Supply. We use the Census 2011 VD indicator of domestic electricity access to define a binary variable, $Access_v$, which equals one if a village reports having domestic electricity supply and zero otherwise. To capture administrative measures of reliability, we use the reported average daily summer hours of domestic electricity supply, denoted $AdminHours_v$. Because this variable is only reported for electrified villages, we code $AdminHours_v = 0$ for villages without reported access, thereby incorporating the extensive margin of electrification.

2. Satellite-Based Reliability ($PrLit$). Our primary outcome is the Proportion of Nights Illuminated, $PrLit_{v,t}$, drawn from the HREA dataset. Following Min et al. (2024), $PrLit_{v,t}$ measures the share of nightly satellite observations in a given year for which a village's detected light output exceeds a background noise threshold. We interpret this measure as capturing the *reliability* of electricity supply—the intensive margin of service delivery—rather than nominal grid connectivity.

Unlike traditional night-time light intensity measures, $PrLit$ relies on a background-noise removal procedure that binarizes nightly illumination outcomes. To ensure these probabilistic measures are not confounded by environmental variance, the underlying signal is corrected using NASA's Black Marble lunar and radiometric reflectance models. These models subtract variations in light intensity caused by the lunar cycle and atmospheric scattering, ensuring that detectable illumination is attributable to terrestrial electricity rather than moonlight or solar glint. This refined daily time-series imagery allows for the detection of faint but persistent electrification signals typical of small and remote settlements without conflating reliability with appliance ownership or income levels. Consequently, a brightly lit urban village and a dimly lit tribal village are treated equivalently, provided that both exceed the sensor's detection threshold on a given night.

Two potential concerns merit discussion. First, Gibson et al. (2021) caution against using night lights as proxies for economic output in rural areas. Our approach is fundamentally different: we use the probabilistic presence of light rather than raw radiance, thereby avoiding the ambiguity of low-radiance values that complicate income estimation.[2] Second, while night-time illumination could in principle reflect off-grid sources such as diesel generators,

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[2] The HREA dataset also provides measures of night-time light intensity (radiance) and a composite light score that combine information on brightness and spatial extent. We do not use these measures because they proxy electricity use intensity and economic activity rather than the reliability of electricity supply, which is the focus of this paper. As Min et al. (2024) note, radiance measures are mechanically sensitive to asset ownership (e.g., the number of bulbs per household), which correlates with income rather than grid quality.

such technologies are unlikely to operate at the spatial and temporal scale required to generate persistent signals during the VIIRS overpass window.[3] Indeed, the late-night overpass timing (approximately 1:30 a.m.) is advantageous for our research question: by observing villages during these hours, we minimize the noise of varying private consumption patterns and isolate the presence of a functioning grid connection — since any detectable light at this hour indicates that electricity is being supplied to the settlement. Prior validation confirms that probabilistic illumination measures closely track grid electricity availability in India and outperform demographic-only models in predicting administrative supply hours (Min et al., 2024; Dugoua et al., 2022).

2.1.2 Demographic Structure: Spatial Segregation of Marginalized Groups

A critical distinction in the political economy of caste is how the spatial segregation of disadvantaged groups shapes access to public goods, with geographic exclusion translating directly into service exclusion. Table 1 documents two fundamentally different—and largely non-overlapping—settlement patterns for ST and SC, with important implications for how exclusion operates.

Tribal enclaves (ST). Scheduled Tribes are characterized by extreme spatial concentration. As shown in Panel A of Table 1, 66.3% of the rural ST population resides in villages where they constitute the absolute majority ($> 50\%$). Crucially, this segregation often reaches extreme levels: more than a third (34.9%) of the rural tribal population lives in hyper-segregated enclaves where the ST share exceeds 90%. This creates a distinct set of nearly 60,000 villages where administrative isolation is absolute. Unlike mixed settlements, these homogeneous demographics allow electricity provision to be deprioritized at the village or feeder level, facilitating whole-village exclusion.

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[3] The HREA measures are derived from VIIRS observations collected between 11 p.m. and 4 a.m. local time to exclude twilight. The Suomi-NPP satellite follows a sun-synchronous orbit with a nominal overpass time of approximately 1:30 a.m. local solar time.

Dalit dispersion (SC). Scheduled Castes, by contrast, exhibit pronounced spatial dispersion. As shown in Panel A of Table 1, only 18.8% of the SC population lives in SC-majority villages, and only a small proportion of SCs (2.5% of the SC population) lives in villages where they constitute >90% of residents. Instead, the overwhelming majority reside in demographically mixed villages where they form a minority share—most commonly between 10–25% of the population. This pattern reflects historical settlement arrangements in which Dalit households are embedded within otherwise non-marginalized villages, often concentrated in segregated hamlets (Asher et al., 2025). Because these hamlets are physically adjacent to the main settlement and often share the same feeder infrastructure, it is technically difficult to ration supply to SC households without simultaneously denying service to the dominant groups.[4]

Mutually exclusive geographies. These SC and ST settlements are not only distinct but also spatially segregated from each other. Figure 1 illustrates this divergence by plotting the spatial distribution of the SC and ST population shares in all villages. Visualizing the data reveals a striking contrast in settlement structure: while Panel (a) shows that the SC population is geographically diffused—appearing as a ubiquitous presence—Panel (b) reveals that the ST population is spatially sequestered, visible as distinct, high-density clusters in the central tribal belt and northeastern regions, separated by vast areas of near-total absence. Panel B of Table 1 demonstrates this near-total separation using cross-group isolation metrics. We find that in SC-majority villages, the average tribal population share is a negligible 2.4%. Conversely, in ST-majority enclaves, the average SC share is only 3.1%. Furthermore, 87.4% of the SC population lives in villages with minimal ST presence ($< 10\%$), while 73.3% of the ST population resides in villages with minimal SC presence ($< 10\%$). Panel C confirms this near-complete separation: SC and ST population shares are strongly

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[4] Our analysis relies on village-level aggregation and cannot detect potential within-village disparities between hamlets. However, unlike urban settings where residential segregation often aligns with distinct distribution transformers or sub-feeders, rural electricity distribution typically involves a single feeder serving the entire village settlement. Consequently, rationing supply to a specific SC hamlet is technically infeasible without cutting power to the shared infrastructure that serves the entire village.

negatively correlated across villages (ρ = -0.35). Whether measured in absolute counts or population shares, the two groups occupy systematically different geographic spaces. This spatial sorting implies that when we separately estimate coefficients for SC-Share and ST-Share within the same district, we are effectively comparing distinct sets of villages rather than examining overlapping disadvantage. Consequently, any divergence in their estimated penalties reflects genuine differences in how exclusion operates across these two settlement structures, rather than confounding from shared geography or correlated group presence.

Mechanism: We argue that the logic of spatial targeting—recently documented at the neighborhood level (Asher et al., 2025)—scales up to the electricity grid.[5] Just as local governments may withhold a clinic from a segregated hamlet, distribution companies may deprioritize maintenance and supply to feeders serving demographically marginalized villages. In this setting, the relevant unit of exclusion is no longer the neighborhood, but the village itself.

Implications for empirical design. These descriptive facts motivate our empirical strategy. Rather than collapsing caste-based marginalization into a single index, we define two separate continuous regressors capturing share of SC (SC_Share_{vd}) and ST (ST_Share_{vd}) in total village population. This distinction allows us to distinguish settings where public services can be withheld at the village or feeder level from those where service denial would impose costs on dominant groups.

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[5] Specifically, Asher et al. (2025) show that public facilities such as secondary schools and health clinics are systematically less likely to be located in SC-majority neighborhoods. We conduct our analysis at the village level because, as noted by Asher et al. (2025), digitized enumeration-block polygon boundaries are not publicly available for rural India; these boundaries are typically held as hand-drawn census maps and are costly to acquire and digitize at scale. Furthermore, while high-resolution satellite data can identify settlements, the extreme granularity and smaller sizes of rural settlements create a scale mismatch with the HREA data itself, which constructs probabilistic illumination measures on approximately 500 m × 500 m grid cells. This spatial resolution is often comparable to or coarser than the footprint of individual rural hamlets, making it infeasible to distinguish electricity provision across sub-village neighborhoods. Consequently, the village remains the most robust unit for auditing service delivery.

2.2 Descriptive Statistics

Table 2 reports summary statistics for the village-level sample. Panel A illustrates the central paradox of Indian electrification: while official coverage is widespread, service remains inadequate. Based on Census 2011, 87.8% of villages report having access to domestic electricity, yet the average village receives only 10.5 hours of supply per day during the summer months. The high standard deviation in supply hours (6.8 hours) underscores the extreme inequality in discretionary administrative provision. Satellite data corroborate this reliability deficit: the mean probability of night-time illumination ($PrLit$) was 0.547 in 2012, rising to 0.662 by 2019. While this indicates substantial improvement over the period, it reveals that even in 2019, the average village remained unlit for approximately one-third of the cloud-free nights observed by the satellite. Panel B confirms that the sample contains the substantial demographic variation required for identification. The average village has a SC population share of 17.6% (s.d. 0.21) and a ST share of 19.4% (s.d. 0.33).[6]

Panel C of Table 2 highlights the geographic heterogeneity of the sample. Villages are on average 23 km from the nearest town and 50 km from the district headquarters, with significant variation in mean elevation and terrain ruggedness. Notably, forest land accounts for 7% of the average village area, a critical control for isolating the tribal service deficit from the technical and statutory challenges of maintaining power lines in wooded terrain. Finally, Panel D serves as our "State Capacity Audit." We find that 81.9% of villages have a government primary school and over half possess a PDS shop, confirming that the state has successfully reached the vast majority of settlements in our sample with essential public services. We return to these variables in Section 3, where we exploit this variation as a "state capacity audit" to distinguish supply-side rationing of electricity from general administrative inaccessibility.

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[6] The mean village-level ST share (19.4%) is higher than the aggregate rural ST population share (≈11.3%) because STs are disproportionately concentrated in small, homogeneous settlements that drive up the *unweighted* village average. In contrast, the village-level SC mean (17.6%) closely tracks their aggregate population share (≈18.5%), reflecting their dispersion across settlements of all sizes.

2.3 Spatial Distribution of Electricity Reliability

Figure 2 displays administrative measures of electricity provision from the 2011 Census VD, with panel (a) indicating reported access to domestic electricity and panel (b) reporting average daily hours of electricity supply during the summer period (April–September). Figure 3 illustrates the spatial distribution of satellite-measured electricity reliability across Indian villages in 2012 and 2019. Despite near-universal reported access, large contiguous regions remain persistently dark at night, particularly in the central tribal belt and eastern India. Crucially, these dark patches spatially mirror the tribal agglomerations documented in Figure 1, while being largely absent from regions of dispersed SC settlement. These visual correlations motivate our focus on within-district comparisons to sharpen inference on the penalty associated with tribal villages.

3 Empirical Strategy

Our empirical strategy examines whether socially segregated villages experience systematically lower electricity reliability even when they share the same district-level infrastructure. We implement this strategy using a village-level regression framework that compares electricity outcomes across villages within the same district that differ in social composition.

$$Y_{vd} = \alpha + \beta_{SC} SC\_Share_{vd} + \beta_{ST} ST\_Share_{vd} + \gamma \mathbf{X}_{vd} + \delta_d + \varepsilon_{vd} \tag{1}$$

where Y_{vd} represents an electricity outcome for village v in district d, SC_Share_{vd} and ST_Share_{vd} represent the share of SC and ST in the village population, respectively. The coefficients of interest, β_{SC} and β_{ST}, capture how electricity provision varies with the village shares of SC and ST populations, respectively.

The vector $\mathbf{X}_{vd}$ includes two primary sets of controls designed to isolate deliberate rationing from environmental and logistical constraints. The first set of controls focuses on the physical geography and logistical complexity of service delivery. By accounting for the logarithm of population, village area, and built-up surface density, we ensure that estimated gradients are not mechanically driven by settlement scale or housing compactness. To address the physical cost of infrastructure maintenance, we further saturate the model with topographic controls, including mean elevation, terrain ruggedness (TRI), presence of all weathered road, and forest land share. These variables allow us to distinguish social exclusion from the higher marginal costs associated with maintaining lines in hilly, uneven, or heavily wooded terrain. We supplement these with distances to urban markets (nearest town) and administrative centers (district headquarter) to ensure the tribal penalty reflects structural exclusion rather than the generic logistical costs of servicing peripheral locations.[7]

The second set of controls addresses administrative visibility and state capacity. We include indicators for government primary schools, health centers, and PDS shops as a "state-capacity audit." By conditioning on villages that fall within the state's operational footprint—proxied by the presence of other administered public goods—we isolate electricity reliability as a distinct margin of discretionary provision. This addresses the concern that tribal deficits merely reflect a "hard-to-reach" problem: if a village can host a school, a functioning health facility, and a PDS outlet—and is connected to the grid—then persistent failures in reliable electricity are more plausibly driven by supply-side prioritization and rationing than by administrative impossibility. Crucially, unlike these largely stock investments, electricity reliability is a flow outcome shaped by repeated operational choices (maintenance, load allocation, and feeder-level management), which are inherently more susceptible to discretionary neglect.

The inclusion of district fixed effects (δ_d) ensures that identification is derived from comparisons within the same administrative and infrastructure environment.[8] This addresses

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[7] For a small fraction of villages with missing distance data, we impute the value using the district median and include an indicator for missingness.

[8] Electricity distribution in India is managed by state-owned Distribution Companies (DISCOMs), which operate at the state or sub-state level. While DISCOM operational boundaries do not perfectly align with district boundaries, districts within the same state are typically served by the same or closely coordinated DISCOM infrastructure, making the district a reasonable unit for absorbing variation in grid capacity and operational practices.

the concern that geographic terrain, regional climate, or state-level policies influence public good provision (Banerjee and Somanathan, 2007). By design, district fixed effects absorb all time-invariant district-level characteristics—including average grid capacity, historical investment, political jurisdiction, and climatic conditions—while our village-level controls account for local heterogeneity. Consequently, the estimated coefficients represent differential electricity provision across villages served by the same district-level feeders and governance environments. This setup directly tests the technical excludability hypothesis: whether the electricity authorities/administrators uses the spatial homogeneity of certain settlements to selectively ration supply. Standard errors are clustered at the district level to account for the spatial correlation of grid infrastructure and the centralized nature of electricity distribution management within districts.

3.1 Dynamics of Change

To examine whether caste-based reliability gaps narrowed or widened during India's post-2011 electrification expansion, we estimate first-difference specifications for the change in outcomes between 2012 and 2019. Following Banerjee and Somanathan (2007), we control for the initial level of public goods provision to distinguish mechanical mean reversion—whereby villages with lower starting levels appear to grow faster due to measurement noise—from genuine conditional convergence. The estimating equation is:

$$\Delta Y_{vd} = \theta Y_{vd,2012} + \beta_{SC} SC\_Share_{vd} + \beta_{ST} ST\_Share_{vd} + \gamma \Delta BuiltUp_{vd} + \lambda \mathbf{X}_{vd} + \delta_d + \varepsilon_{vd}, \quad (2)$$

where $\Delta Y_{vd} = Y_{vd,2019} - Y_{vd,2012}$. We include the baseline reliability level ($Y_{vd,2012}$) to test for conditional convergence ($\theta < 0$). We control for the change in built-up density ($\Delta BuiltUp_{vd}$) to account for differential physical expansion over the study period, while $\mathbf{X}_{vd}$ denotes baseline village characteristics measured in 2011. District fixed effects (δ_d) absorb all time-invariant district-level factors, ensuring that identification comes from differential changes across villages within the same administrative unit.

A standard econometric concern in convergence specifications is that measurement error in the baseline outcome ($Y_{vd,2012}$) can mechanically induce spurious mean reversion, a phenomenon known as Galton's Fallacy (Friedman, 1992). If baseline reliability is measured with error, this noise biases the convergence coefficient (θ) downward. Furthermore, because baseline reliability is correlated with village demographics, this bias can be transmitted to the coefficients of our primary variables of interest (β_{SC} and β_{ST}). To address this concern, we employ an instrumental variables (IV) strategy. We instrument the satellite-derived baseline outcome ($Y_{vd,2012}$) using two independent measures of electricity provision from the 2011 Census: (i) average daily hours of domestic electricity supply during the summer months ($AdminHours_{vd,2011}$), and (ii) a binary indicator capturing village electricity access ($Access_{vd,2011}$). Because these administrative measures are collected independently of the satellite imaging process, their measurement errors are plausibly uncorrelated with errors in the satellite data. We report results from exactly identified specifications (using each instrument separately) as well as an overidentified specification using both instruments jointly, assessing the validity of the exclusion restriction via the Hansen J test.

3.2 Measuring Energy Poverty Risk

Although electricity is not the only energy source that matters to a household, access to minimum levels of reliable and affordable electrical power is a critical component of most widely used measures of energy poverty (Nussbaumer et al., 2012; Bhatia and Angelou, 2015; Min et al., 2024). To explicitly measure the prevalence and persistence of energy deprivation, we define a set of binary indicators for *Energy Poverty* based on the relative distribution of reliability. A village v is classified as energy poor in year t if its reliability score ($PrLit_{vd,t}$) falls below a specific threshold τ. To ensure our poverty benchmarks are grounded in the empirical distribution of the sample, we anchor τ to the 10th, 20th, and 30th percentiles of the national reliability distribution at the start of our study period in

2012 ($P_{10} = 0.12, P_{20} = 0.24, P_{30} = 0.36$). We then estimate the risk of falling into these poverty brackets using a linear probability model:

$$\Pr(Poor_{vd,t} = 1) = \alpha + \beta_{SC} SC\_Share_{vd} + \beta_{ST} ST\_Share_{vd} + \gamma \mathbf{X} vd + \delta d + \varepsilon_{vd} \qquad (3)$$

where $Poor_{vd,t} = \mathbf{1}(PrLit_{vd,t} < \tau)$. We utilize these fixed 2012 thresholds to analyze both the cross-sectional risk in 2012 and 2019. A positive β_{ST} in this specification indicates that ST-majority villages face a systematically higher risk of falling into the bottom tail of the reliability distribution than non-ST villages served by the same district-level infrastructure.

3.3 Mobility and Poverty Traps

Finally, we test for the existence of structural poverty traps by examining the conditional probability of escaping energy deprivation. This dynamic specification allows us to observe whether the massive grid expansion of the 2010s was inclusive of the most marginalized settlements or if tribal enclaves remained structurally "anchored" to the bottom of the reliability distribution. We define a binary indicator $Escaped_{vd}$ equal to one if a village's reliability score in 2019 exceeded the baseline threshold, conditional on that village having been classified as energy poor in 2012. We estimate:

$$\text{Escaped}_{vd} = \alpha + \beta_{SC} \text{SC\_Share}_{vd} + \beta_{ST} \text{ST\_Share}_{vd} + \gamma \mathbf{X}_{vd} + \delta_d + \varepsilon_{vd} \quad \text{if} \quad \text{PrLit}_{vd,2012} < \tau \quad (4)$$

where τ represents the 10th, 20th, or 30th percentile of the 2012 baseline distribution (P_{10}, P_{20}, P_{30}). The coefficients β_{SC} and β_{ST} measure the marginal change in the probability of crossing the threshold by 2019, relative to a general-category village in the same district that started at the same level of deprivation.

A negative β_{ST} in this specification provides direct evidence of a mobility trap. It indicates that even when we control for identical starting conditions and administrative visibility, tribal enclaves face higher structural barriers to reliability upgrades. This setup tests whether tribal enclaves— despite starting from identical levels of deprivation— face persistent structural barriers to reliability upgrades, even as national grid capacity expands around them.

3.4 Testing for Non-Linearity and Enclave Effects

The baseline specification assumes that the penalty for marginalization grows linearly with population share. However, qualitative evidence suggests that exclusion may be structural, targeting specific settlements that are administratively identified as Tribal or Dalit enclaves. To test for such threshold effects, we estimate a non-parametric specification where we replace the continuous population shares with categorical indicators based on demographic concentration:

$$Y_{vd} = \alpha + \sum_{k=2}^{5} \beta_{SC}^{k} \mathbf{1}(\text{SC\_Cat}_{vd} = k) + \sum_{k=2}^{5} \beta_{ST}^{k} \mathbf{1}(\text{ST\_Cat}_{vd} = k) + \gamma \mathbf{X}_{vd} + \delta_d + \varepsilon_{vd} \tag{5}$$

where k indexes five distinct demographic bins: $< 30\%$ (Reference Category), $30 - 50\%$, $50 - 70\%$, $70 - 90\%$, and $90 - 100\%$ (Homogeneous Enclave).

The coefficients of interest are β_{SC}^{k} and β_{ST}^{k}, which capture the reliability differential for villages at different levels of concentration of SC and ST relative to the reference group ($< 30\%$). A sharp jump in the coefficient for the majority bin ($k > 50\%$) would provide evidence of an Enclave Penalty—a structural disadvantage associated with majority SC or ST villages within the same district.

4 Results

Table 3 contrasts the Census 2011 measure of connectivity with actual service delivery. In Panel A, we focus on the access gap. Column (1) establishes a baseline within-district comparison, controlling for (log) population and area while absorbing district fixed effects. The coefficients on SC and ST share terms exhibit a notable divergence.[9] While β_{SC} is positive but effectively zero, the β_{ST} is negative and relatively large (-0.088), reflecting a severe disadvantage for tribal settlements even when compared to neighboring villages in the same district. This specification effectively contrasts the outcomes of Tribal Enclaves (100% ST) against the district's non-SC/ST populated villages, exploiting the spatial segregation documented in Table 1. In Column (2), we introduce geography controls: distance to the nearest town and district headquarter, mean elevation, terrain ruggedness (TRI), forest land share and the presence of an all-weather road. While these controls account for approximately 30% of the ST penalty—moving the coefficient from -0.088 to -0.061—the remaining deficit is economically large and highly significant. This indicates that while remoteness and physical terrain are contributing factors, they are not the primary drivers; a substantial tribal penalty persists that cannot be attributed to the geographic or logistical complexity of service delivery.

In Column (3), we add a control for built-up density to account for physical settlement structure. This inclusion leaves the coefficients virtually unchanged, confirming that the access deficit is not mechanically driven by differences in physical density or settlement compactness (e.g., the higher cost of wiring dispersed hamlets). In Column (4), we introduce a vector of administrative visibility controls, including the presence of government primary schools, primary health centers, and PDS shops. These serve as a falsification test for state capacity; if the state can successfully deliver schools and clinics to these enclaves, the absence of electricity is unlikely to be a result of administrative invisibility. Even in this saturated model, the ST (100% ST) penalty persists at -0.063. This implies that even when sharing the same district administration and possessing the same level of institutional infrastructure, a fully tribal village is 6.3 percentage points less likely to have electricity access than a non-tribal neighboring villages.

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[9] The regression sample ($N = 551,364$) is smaller than the total number of villages reported in Table 2 because the Census VD contains missing records for access and hours of supply for a small fraction of villages, with missing information being most pronounced in the states of Karnataka and Chhattisgarh.

Panel B of Table 3 shifts the focus from the stock of infrastructure (access) to the flow of service (supply hours). In this specification, we assign zero hours to villages reporting no electricity access to capture the total deficit in service provision. Here, the divergence is even more pronounced. In Column (4), which isolates within-district variation and controls for all administrative and geographic factors, the coefficient on SC share is statistically indistinguishable from zero ($\beta_{SC} = 0.048$). Conversely, the penalty for ST remains large, negative, and statistically significant ($\beta_{ST} = -0.824$). This estimate implies that a fully tribal enclave receives approximately 50 minutes (0.824 hours) less electricity per day than a non-tribal neighbor within the same district. This total service gap reflects both the lower probability of being connected to the grid and the lower reliability of supply for those that are. To disentangle whether this is driven solely by a lack of access or by lower reliability for those already connected, we re-estimate the full specification restricting the sample to electrified villages only. We find that even conditional on having grid access, tribal enclaves face a statistically significant supply deficit of approximately 11 minutes per day ($\beta = -0.191$; $p = 0.014$).[10] This confirms that the ST enclave penalty operates on both the extensive margin (access) and the intensive margin (reliability). The persistence of this gap—even among villages with identical administrative visibility and physical infrastructure—is consistent with a pattern of systematic rationing away from tribal settlements.

Table 4 utilizes satellite-derived probability of illumination ($PrLit$) to measure de facto reliability. We begin in Column 1 by estimating the baseline penalty conditional on village scale (population and area) and district fixed effects.[11] Even after accounting for within-district variation and adjusting for the fact that tribal villages may differ in size or land area, we observe a large negative coefficient ($\beta_{ST} = -0.186$ in Panel A). We then assess the role of geography and settlement structure. Controlling for geography in Column 2 reduces

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[10] For space considerations, we do not report this specification in the main text.

[11] The regression sample for satellite-based outcomes ($N = 566,966$) is larger than the official administrative sample, as remote sensing bypasses the reporting gaps in the Census Village Directory. Following HREA data quality protocols, the metric is only reported for villages with a sufficient number of cloud-free nightly observations to ensure statistical robustness of the probabilistic measure.

the magnitude of the tribal penalty to −0.109. While geography and remoteness account for approximately 40% of the ST penalty, the remaining deficit is economically large and highly significant. Adding built-up density in Column 3 further refines the coefficient to −0.096. This pattern suggests that while the remoteness and lower settlement density of tribal areas are important factors, a large, structural penalty persists even when comparing villages of identical size, density, and location.

In Column 4 of Table 4, we introduce the administrative visibility controls. Even when comparing villages that have reached the same threshold of state presence, a severe structural deficit remains. In 2012 (Panel A), tribal enclaves were 9.3 percentage points less likely to be illuminated on a given night than their non-tribal neighbor villages. Given the sample mean reliability of 0.547 in 2012, this coefficient implies that tribal villages faced an 17% reliability deficit relative to non-tribal villages. In practical terms, while the average village was lit for about 200 nights a year, a comparable tribal enclave was left in the dark for roughly 36 additional nights. Crucially, despite the massive expansion of the grid between 2012 and 2019, this penalty did not converge. In 2019 (Panel B), the within-district coefficient in the saturated model actually widened slightly to −0.104. Although the average village reliability improved to 0.662 during this period, the tribal penalty remained proportionally severe, representing a 15.7% deficit relative to the new mean. This indicates that while the tide of electrification rose, it did not lift tribal boats equally; even in 2019, tribal enclaves continued to lag significantly behind the national reliability standard, suggesting that the "Saubhagya" era of universal household electrification did not close the intensive margin gap for marginalized enclaves.

Table 5 estimates the dynamics of change using a first-difference specification, controlling for initial reliability to distinguish structural trends from natural mean reversion. In all specifications (Columns 1–4), the coefficient on initial reliability is consistently negative and significant (β ranging from −0.24 to −0.32), confirming a strong overall mean reversion: villages that started in the dark generally experienced faster catch-up growth. However, tribal villages were systematically excluded from this convergence process. The coefficient on ST Share is negative and economically significant in the preferred OLS specification ($\beta_{ST} = -0.042$, Column 1). To put this in perspective, while the average village saw reliability improve by approximately 11.5 percentage points over this period, a fully tribal village experienced 4.2 percentage points less growth than its non-tribal neighbor. This implies that tribal enclaves captured significantly fewer reliability gains than the rest of the district.

Crucially, this result is not driven by measurement error in the baseline (Galton's Fallacy). Across the Instrumental Variable specifications (Columns 2–4)—which instrument baseline reliability using 2011 Census access and hours of supply—the ST penalty remains remarkably stable, ranging from -0.036 to -0.044. These IV models successfully pass the overidentification test ($p = 0.195$), suggesting the instruments are valid and the results are not biased by mean-reversion artifacts. In sharp contrast, the coefficient for SC share is statistically indistinguishable from zero in the fully controlled models. This suggests that unlike tribal enclaves, Dalit hamlets are successfully tracking the general convergence trend of the district. The divergence is thus specific to tribal villages, highlighting a stark contemporary contrast: while villages with Dalit hamlets are integrated into the district's convergence path, tribal enclaves systematically lag behind the district's trajectory.

4.1 Structural Persistence and Mobility Traps

The segmented convergence documented in Table 5 raises a critical question: does this slower growth merely delay development, or does it actively trap tribal communities in a state of deprivation? To answer this, Table 6 moves beyond average reliability to examine energy poverty using data-driven benchmarks. Table 6 provides our most direct test of structural exclusion through the lens of a mobility trap. Panels A and B show that ST villages are significantly more likely to reside in the lower tail of the distribution. Even after conditioning on district fixed effects, administrative visibility, and the full vector of geographic controls, ST envlaves (100% ST) were 11.6 percentage points more likely to suffer from extreme energy poverty ($< P_{10}$) in 2012. By 2019, despite the "Saubhagya" era's push for universal access, this risk remains high at 7.6 percentage points. For the moderate poverty threshold ($< P_{30}$), the ST penalty remains virtually unchanged over the decade (moving from 15.6 to 14.9 percentage points), indicating that tribal disadvantage does not dissipate with overall improvements in national grid reliability.

Panel C of Table 6 delivers the central result of this study. Restricting the sample to villages that were energy-poor in 2012, we examine the probability of escaping that status by 2019. We find a large and economically meaningful mobility penalty: conditional on starting in extreme poverty, ST-majority villages were 9.0 percentage points less likely to escape than equally poor non-ST villages within the same district. This "sticky" deprivation is even more pronounced at the P_{20} and P_{30} thresholds, where the escape probability is roughly 11.7 and 12.2 percentage points lower for tribal settlements. These results effectively reject the hypothesis that tribal disparities reflect only adverse initial conditions; instead, they point to an active and ongoing exclusion that prevents upward mobility even among villages starting from identical levels of baseline deprivation.

Taken together, Tables 5 and 6 results identify a dual burden unique to tribal settlements: persistent exposure to energy poverty and sharply constrained mobility out of it. In contrast, SC villages largely track district-level convergence, with coefficients that are small and statistically indistinguishable from zero.

4.2 Heterogeneity by Composition: The Gradient of Exclusion

Table 7 summarizes the non-linear nature of exclusion across our primary dimensions of electricity provision: official supply, satellite-measured reliability, energy poverty risk, and upward mobility. By disaggregating demographic composition into distinct bins, we test whether exclusion emerges at simple majority thresholds or intensifies with increasing demographic homogeneity. The results reveal a striking dose-response relationship: as villages approach total homogeneity with respect to the ST population, the penalty intensifies sharply.

Conversely, we find no such negative gradient with respect to SC population share. Based on 2011 Census measures, the Enclave Effect is immediately apparent. While mixed-majority villages (ST share 50%–70%) face no statistically significant deficit in official access, homogeneous ST enclaves (90%–100%) are 7.7 percentage points less likely to be connected compared to villages within the same district where the ST population is less than 30%. The intensive margin of official supply (Column 2) follows an even steeper pattern: ST enclaves with more than 90% ST population report receiving approximately 1.05 hours less electricity per day than the reference group, a gap that is largely absent in mixed-tribal settings.

Columns 3–4 of Table 7 demonstrate that the satellite-measured reliability gap increases sharply with ST population share. In 2012, the penalty grows from a 1.3 percentage point deficit in villages with 30%–50% ST share to a 9.9 percentage point deficit in homogeneous enclaves ($\geq$ 90% ST); by 2019, this enclave penalty widens to 10.7 percentage points. The presence of even a modest non-tribal minority thus appears to attenuate the deficit, consistent with greater administrative visibility and political contestability in more mixed settlements. The pattern is not only monotonic but also markedly non-linear, with a discrete increase as villages approach near-total tribal homogeneity.

Columns 5–6 report the results for energy poverty risk, using the 30th percentile (P_{30}) of the baseline distribution (2012) as a threshold. We observe a monotonic increase in poverty risk: fully tribal enclaves face a 16.6 and 16.0 percentage point higher probability of being energy poor in 2012 and 2019, respectively. Perhaps most critically, these villages exhibit a pronounced mobility trap. As shown in Column 7, conditional on starting in energy poverty in 2012, homogeneous tribal enclaves are 11.7 percentage points less likely to escape deprivation by 2019 than otherwise comparable non-tribal villages within the same district. The enclave structure that enables supply-side rationing thus has cumulative consequences: it not only depresses reliability at a point in time but actively prevents upward mobility out of energy poverty, even as national grid capacity expands.

4.3 Mechanism: Supply-Side Rationing vs. Demand-Side Explanations (interpretation)

In Section 2.1.2, we noted that the spatial structure of tribal settlements — concentrated in homogeneous, administratively distinct villages — creates the technical preconditions for village- or feeder-level exclusion. The results presented above now allow us to assess whether the observed patterns are consistent with this supply-side mechanism or whether they are better explained by demand-side differences across villages.

We do not observe feeder-level dispatch or outage allocation data, and therefore cannot directly trace the administrative channel through which rationing occurs. However, the discrete jump at near-total homogeneity is more naturally consistent with targeting at the level of the administrative settlement (or its feeder catchment) than with purely demand-driven explanations. If differences in demand or willingness-to-pay were the primary driver, one would more naturally expect a smoother gradient within districts; the enclave threshold instead suggests that once a settlement becomes demographically targetable, it can be deprioritized as a whole. Near-total administrative segregation ($> 90\%$ ST) corresponds with the most severe reliability deficits because these units can be bypassed by discretionary supply management with limited political blowback from other groups. Crucially, this penalty is unique to tribal settlements: as reported in Panel B, SC-concentrated villages face no comparable gradient at higher levels of SC share.

These patterns also help adjudicate between supply-side and demand-side explanations for the tribal reliability deficit. A plausible alternative interpretation is that ST enclaves have lower electricity demand— owing to lower incomes, fewer appliances, and less commercial activity— which reduces the utility's revenue incentive to maintain reliable supply. This would be consistent with the subsidy trap dynamics described by McRae (2015), whereby low collection rates in underserved areas create a self-reinforcing cycle of poor service and low willingness to pay. We take this alternative seriously but note several features of our results that are difficult to reconcile with a purely demand-driven account.

First, our primary outcome — the probability of illumination — captures the binary presence of detectable light rather than consumption intensity. As Min et al. (2024) emphasize, this measure is insensitive to appliance ownership or household income. A demand-driven explanation would more naturally predict variation in light intensity rather than in the probability of any light at all. The fact that entire villages show zero illumination on a substantial share of nights suggests that the grid is simply not delivering power, regardless of what demand might exist. Second, our specifications control for log population, log area, built-up density, distance to nearest town and district headquarter, mean elevation, terrain ruggedness, and forest land share — absorbing much of the cross-village variation in commercial activity, economic scale, and the physical cost of infrastructure maintenance. The ST penalty persists even when comparing villages of identical size, density, market proximity, and topographic difficulty within the same district.[12] This ensures that the estimated deficit reflects neither the logistical challenges of serving remote or rugged settlements nor differences in the scale of potential demand.

Third, if low demand were the primary explanation, we would expect SC villages to exhibit a comparable reliability deficit, given that SC households face similar levels of economic deprivation. Yet across every specification. SC villages exhibit no disadvantage relative to the district mean, and in several cases show marginally better outcomes. This sharp divergence between two groups with similar economic profiles but fundamentally different spatial organization strongly suggests that the operative mechanism is not demand but excludability: the same poverty that might depress demand in a tribal enclave also exists in SC hamlets, but those hamlets cannot be selectively rationed because they share feeder infrastructure

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[12] A potential concern is that dense vegetation canopy could both attenuate night-time light signals reaching the VIIRS sensor — mechanically lowering $PrLit$ in forested areas— and increase the cost of maintaining power lines due to vegetation encroachment, storm damage, and restricted access. Since tribal villages are disproportionately located in forested areas, either channel could bias our estimates. To address this, we verify that our results are robust to controlling for satellite-derived vegetation density (MODIS Vegetation Continuous Fields (Dimiceli et al., 2015)), in addition to the Census-based forest land share already included in all specifications. The VCF coefficient is statistically insignificant and its inclusion leaves the estimated ST enclave penalty virtually unchanged, confirming that the tribal reliability deficit is driven by neither canopy obstruction of satellite signals nor the higher maintenance costs associated with dense vegetation.

with dominant-caste neighbors.

Fourth, a pure demand-side explanation cannot easily account for the sharp non-linearity documented above. If lower demand were the primary driver, we would expect the reliability deficit to increase roughly proportionally with ST share, tracking the gradual decline in average village income. Instead, we observe a discrete jump at the enclave threshold (>90% ST), precisely the pattern predicted by a supply-side targeting mechanism that exploits demographic homogeneity. The fact that even a modest non-tribal minority presence substantially attenuates the penalty suggests that the relevant constraint is not aggregate demand but rather the political cost of service denial — a cost that drops sharply when no non-tribal households are affected.

A further reason supply-side rationing can persist in tribal enclaves is that the affected communities face structural constraints on their ability to respond. As Munshi and Rosenzweig (2016) argue, caste and tribal networks, while providing social insurance, also constrain geographic mobility, anchoring marginalized communities to specific locations. This immobility renders tribal settlements particularly vulnerable to discretionary shortfalls in service provision, even within shared district infrastructure, as they are less likely to exit, protest, or impose political or administrative costs on service providers.

Moreover, even India's primary institutional remedy for tribal marginalization — political reservation — does not attenuate the enclave penalty. Appendix Table A1 interacts ST concentration bins with an indicator for ST-reserved Assembly Constituencies, in which only Scheduled Tribe candidates may contest elections. If guaranteed tribal representation improved service delivery, we would expect the interaction terms to offset the ST penalty. Instead, Panel B shows that the interactions are overwhelmingly insignificant, and the few cases of marginal significance offer no evidence of attenuation — if anything, they suggest that ST enclaves in reserved constituencies fare slightly worse.[13] The ST Reserved Seat

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[13] We control for district-fixed effects; in the Indian administrative hierarchy, each district contains multiple assembly constituencies (on average 6.4 ACs per district). This ensures that our estimates are identified from within-district variation between constituencies sharing the same regional administrative and utility infrastructure.

indicator itself is negative and significant for satellite-measured reliability, suggesting that reservation status proxies for deeper structural disadvantage that political representation alone cannot overcome. This finding reinforces the interpretation that rationing operates at the administrative or utility level — through DISCOM maintenance and dispatch decisions — rather than through legislative channels (Pande, 2003). Indeed, Banerjee and Somanathan (2007) show that between 1971 and 1991, Scheduled Castes gained in public goods access after establishing independent political parties, while Scheduled Tribes — who remained electorally loyal to the Congress party and lacked autonomous political leadership — continued to fall behind, suggesting that formal reservation without substantive political mobilization is insufficient to improve service delivery.

We cannot fully rule out the possibility that demand-side factors contribute to the observed gap. However, the combination of a binary outcome measure that is insensitive to consumption levels, saturated controls for economic scale and remoteness, the absence of any comparable penalty for equally poor SC villages, and the distinctly non-linear enclave pattern collectively point toward supply-side discretion as the dominant channel operating beyond what demand differences alone can explain.

5 Conclusion

India's rapid expansion of electricity infrastructure over the past decade has been widely celebrated as a major development achievement. Official statistics suggest that the access gap has largely closed, reinforcing a narrative of convergence in the provision of a critical public good. This paper shows that this narrative is incomplete. While grid connections have become nearly universal, the reliability of electricity supply remains deeply unequal, and these inequalities are structured along persistent social and spatial lines. Unlike static infrastructure such as schools or roads, electricity is a flow: supply can be rationed, adjusted, and curtailed in ways that are far less visible than the initial placement of poles and wires.

As a result, exclusion can persist — and go undetected — even after formal access has been achieved.

Using high-resolution satellite-based measures linked to comprehensive census data, we document a robust and non-linear Enclave Penalty for ST villages. Within the same district, tribal-majority enclaves experience substantially lower electricity reliability — a deficit that cannot be explained by topography, remoteness, or mechanical mean reversion, and that intensifies sharply once a village crosses the threshold of near-total tribal homogeneity. In contrast, SC villages — characterized by spatial dispersion rather than enclave formation — exhibit no such disadvantage, highlighting the central role of spatial segregation in determining who bears the burden of service rationing.

Our identification of the Enclave Penalty mirrors global patterns documented by Min et al. (2024), who find that electricity poverty frequently persists in pockets of sparse settlement even within otherwise electrified regions. We show that in the Indian context, these pockets closely overlap with socially homogeneous tribal settlements. As governments increasingly succeed in expanding access to basic infrastructure, inequality in quality and reliability may become the dominant dimension of exclusion — one that administrative records are poorly equipped to detect. When official data becomes decoupled from reality, as seen in the divergence between Saubhagya's universal access claims and the persistent darkness in tribal enclaves, satellite-based measures provide a critical independent audit of service delivery. Beyond these cross-sectional disparities, the evidence reveals a stark mobility trap: conditional on being energy-poor in 2012, tribal enclaves were far less likely to escape poverty by 2019 than otherwise similar neighbors. The locus of exclusion has thus shifted: from the visible denial of infrastructure to the quieter rationing of service quality.

These findings have direct policy implications. First, India's official electrification monitoring should incorporate satellite-based reliability metrics to independently verify service delivery and identify persistent pockets of deprivation that administrative data may obscure. Second, distribution companies should be required to publicly report feeder-level reliability data disaggregated by village demographics, enabling regulators and civil society to detect and audit systematic rationing patterns. Third, electricity regulatory commissions could adopt differentiated quality-of-service standards with financial penalties for utilities that persistently underserve tribal enclaves. Ultimately, delivering true energy justice requires moving beyond the metric of connectivity to guarantee the quality of service—especially for those sequestered communities where darkness has become a structural condition.

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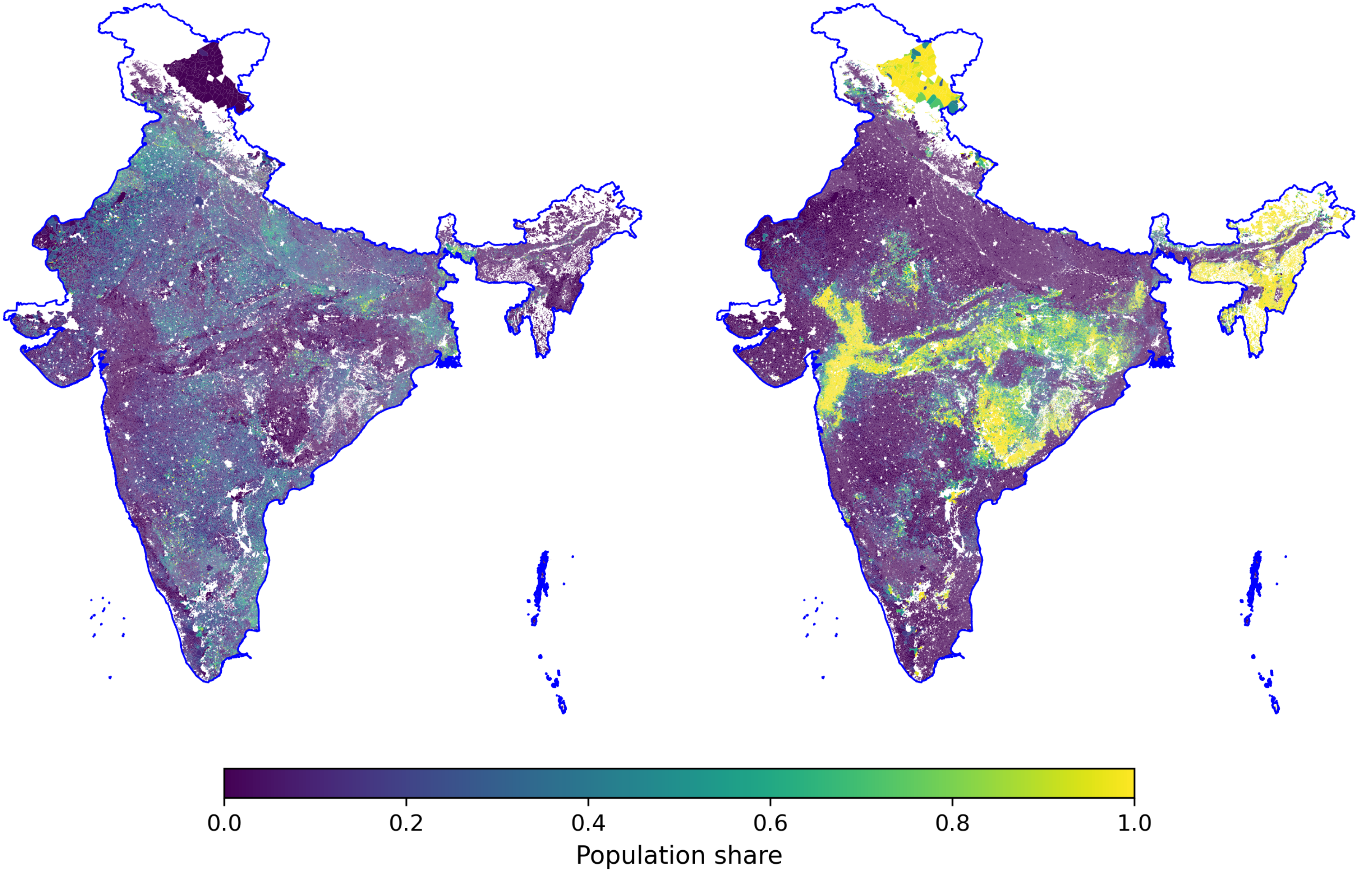
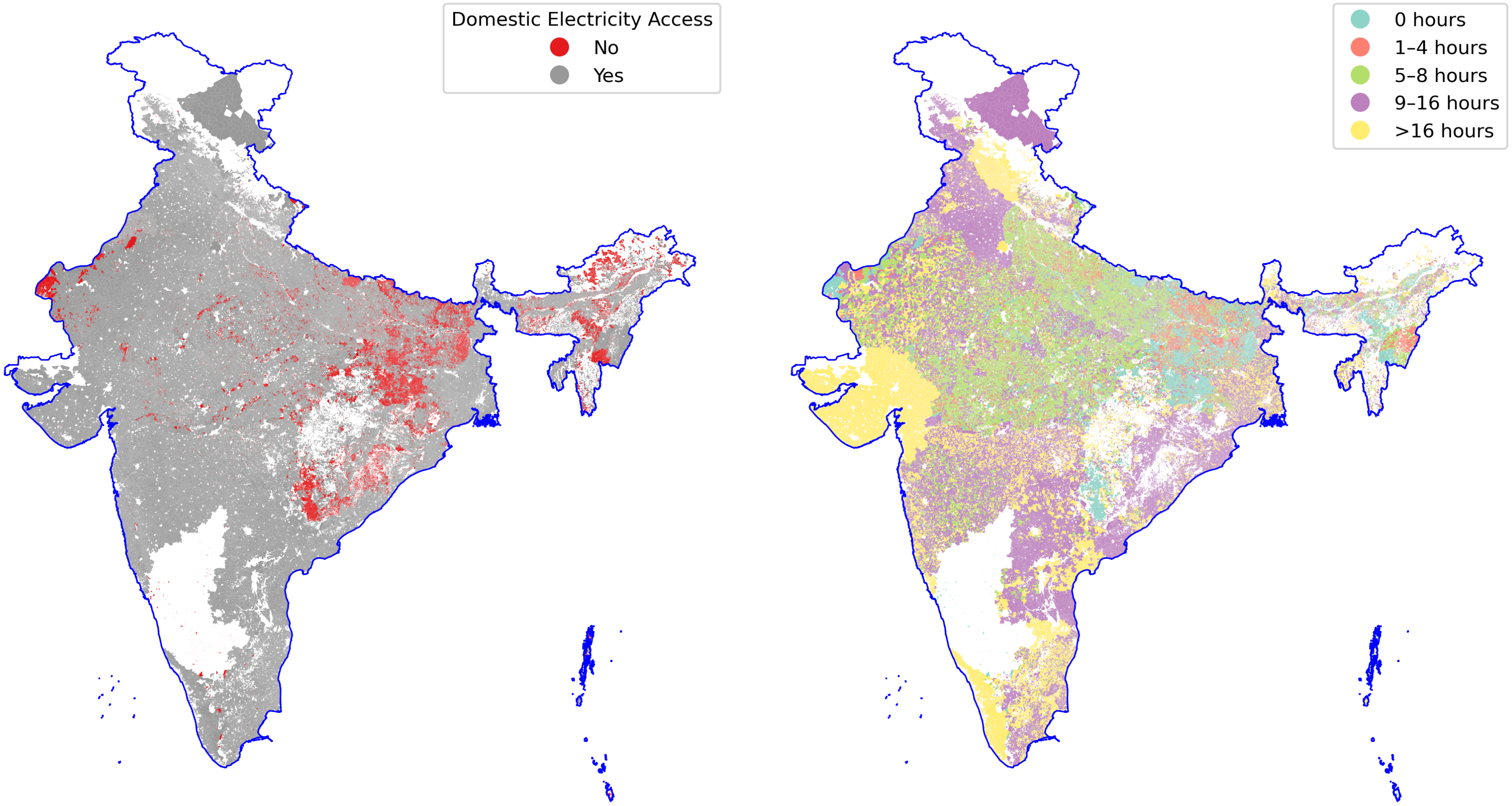
Figure 1: Spatial distribution of Scheduled Caste (SC) and Scheduled Tribe (ST) population shares across villages.



(a) Scheduled Caste share

(b) Scheduled Tribe share

Figure 2: Administrative Measures of Electricity Access and Supply from the 2011 Census

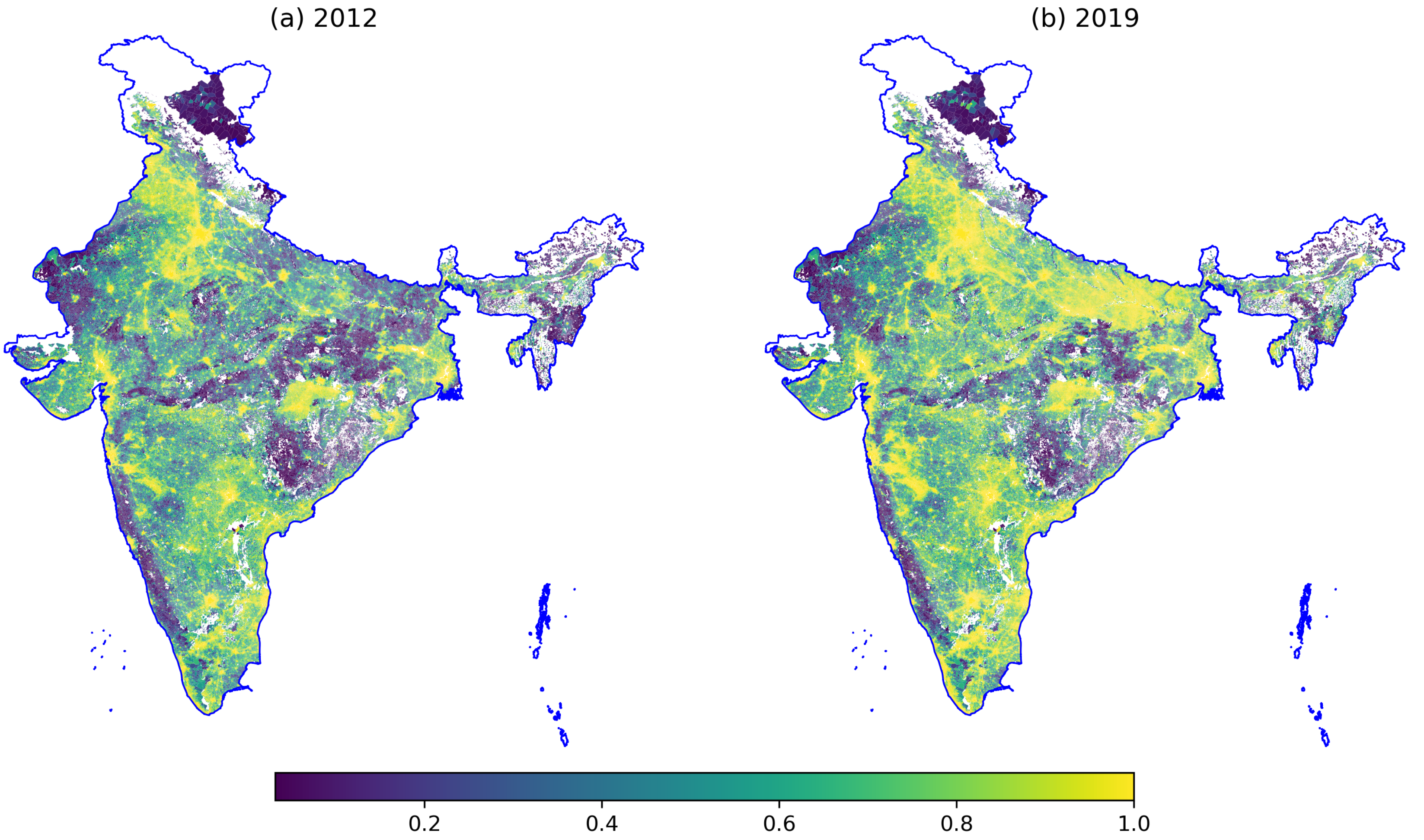


(a) Access to Domestic Electricity

(b) Daily Electricity Supply (Summer, hrs)

Notes: Panel (a) reports a binary indicator equal to one if a village reports access to domestic electricity in the 2011 Census Village Directory. Panel (b) reports Census-reported average daily hours of electricity supply during summer months (April–September). Hours are reported at the village level by local officials. White areas indicate villages with missing Village Directory records. Data coverage issues are more pronounced in the state Karnataka and Chhattisgarh.

Figure 3: Satellite-Based Electricity Reliability (Probability of Illumination)


(a) 2012

(b) 2019

Notes: Spatial distribution of electricity reliability using the satellite-derived *PrLit* metric from the High-Resolution Electricity Access (HREA) dataset. *PrLit* is defined as the proportion of nights a village was observed to be lit above a background noise threshold. It serves as a proxy for the regularity of power supply, with values ranging from 0 (never lit) to 1 (lit every night).

Table 1: Spatial Segregation of Scheduled Castes and Scheduled Tribes

Panel A: Own-Group Distribution (Enclaves vs. Dispersion)

	Scheduled Castes (SC)			**Scheduled Tribes (ST)**		
Group Share in Own Village	**Villages (000s)**	**Pop. (Mil)**	**% of Total SC Pop.**	**Villages (000s)**	**Pop. (Mil)**	**% of Total ST Pop.**
≤ 10%	279.4	11.0	7.2%	407.5	6.4	6.8%
10% – 25%	150.5	52.6	34.2%	40.0	10.1	10.8%
25% – 35%	62.3	31.7	20.6%	16.3	6.1	6.5%
35% – 50%	50.2	29.6	19.3%	19.0	9.0	9.6%
50% – 70%	27.0	17.5	11.4%	21.8	12.9	13.7%
70% – 90%	10.9	7.5	4.8%	24.7	16.6	17.7%
> 90% (Enclaves)	8.5	3.9	2.5%	59.8	32.8	34.9%
Total	589.0	153.8	100.0%	589.0	94.1	100.0%

Panel B: Cross-Group Isolation (Mutually Exclusive Geographies)

	Distribution Across Other Group's Concentration Bins					
Metric	**≤ 10%**	**10–25%**	**25–35%**	**35–50%**	**> 50%**	**Summary**
1. Distribution of ST Population (across SC-share bins)						
% of Total ST Pop.	73.3%	19.0%	4.4%	2.3%	**1.1%**	*STs absent from*
Avg. ST Share in Village	33.8%	8.7%	5.4%	4.2%	**2.4%**	*SC areas*
2. Distribution of SC Population (across ST-share bins)						
% of Total SC Pop.	87.4%	7.0%	2.0%	1.7%	**2.0%**	*SCs absent from*
Avg. SC Share in Village	21.7%	17.7%	14.8%	12.5%	**3.1%**	*ST areas*

Panel C: Spatial Correlation Between Groups

Metric	**Correlation (ρ)**	**P-value**
Absolute Population Counts	-0.030***	0.000
Population Shares	-0.353***	0.000

Notes: Panel A shows the distribution of SC and ST populations across villages grouped by demographic concentration. Panel B demonstrates cross-group isolation by showing where each group lives relative to the other group's concentration (e.g., most STs live in villages with minimal SC presence, and vice versa). Panel C reports the correlation between SC and ST population shares across villages. Data from Census 2011 Village Directory. *** p<0.01.

Table 2: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**N**
Panel A: Electricity Outcomes			
Official Domestic Access (1/0)	0.878	0.327	551,365
Official Summer Supply (Hours/Day)	10.492	6.786	544,356
Probability Lit (Reliability) - 2012	0.547	0.292	566,967
Probability Lit (Reliability) - 2019	0.662	0.296	566,967
Panel B: Demographic Composition			
Share of Scheduled Caste (SC)	0.176	0.207	588,972
Share of Scheduled Tribe (ST)	0.194	0.334	588,973
Panel C: Geography and Topography			
Distance to nearest town (km)	23.118	18.558	440,638
Distance to District HQ (km)	50.423	35.494	545,936
Mean Elevation (Meters)	334.401	401.232	588,973
Terrain Ruggedness Index (TRI)	7.155	8.758	588,973
Forest Land Share	0.070	0.174	588,973
Panel D: Administrative Access (State Capacity)			
Village has Primary School (1/0)	0.819	0.385	588,973
Village has Health Center (PHC) (1/0)	0.043	0.202	588,973
Village has PDS Shop (1/0)	0.505	0.500	588,030

Notes: This table reports summary statistics for the village-level analysis sample. *Official Access*, *Supply*, *Distances*, and administrative indicators are from the Census 2011 Village Directory. *Probability Lit* (0–1) measures the fraction of observed cloud-free nights a village signal exceeded the noise threshold. N varies across rows due to differential reporting in the Census 2011.

Table 3: Official Electricity Provision: Access vs. Supply Hours

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable = Official Access (Binary 0/1)				
Share of SC	0.005	0.002	0.003	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Share of ST	-0.088***	-0.061***	-0.060***	-0.063***
	(0.014)	(0.013)	(0.013)	(0.013)
R-squared	0.401	0.409	0.409	0.411
Observations	551,364	551,364	551,364	551,364
Panel B: Dependent Variable = Official Supply (Summer Hours/Day)				
Share of SC	0.077	0.042	0.065	0.048
	(0.069)	(0.065)	(0.065)	(0.064)
Share of ST	-1.259***	-0.829***	-0.806***	-0.824***
	(0.175)	(0.156)	(0.157)	(0.156)
R-squared	0.700	0.704	0.705	0.705
Observations	544,355	544,355	544,355	544,355
Geography	No	Yes	Yes	Yes
Built-up Density	No	No	Yes	Yes
Administrative Visibility	No	No	No	Yes

Notes: Robust standard errors clustered at the district level in parentheses. All models include district fixed effects and control for village-level (log) population and area. Geography includes distance to district headquarter and nearest town, mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road. Administrative visibility controls include indicators for government primary schools, primary health centers, and PDS shops. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Satellite-Observed Reliability: Persistence of the Gap (2012 vs. 2019)

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable = Probability Lit (2012)				
Share of SC	0.017***	0.013**	0.026***	0.027***
	(0.006)	(0.005)	(0.005)	(0.005)
Share of ST	-0.186***	-0.109***	-0.096***	-0.093***
	(0.013)	(0.009)	(0.010)	(0.009)
R-squared	0.502	0.555	0.588	0.589
Panel B: Dependent Variable = Probability Lit (2019)				
Share of SC	0.014**	0.010*	0.020***	0.022***
	(0.006)	(0.005)	(0.005)	(0.005)
Share of ST	-0.195***	-0.117***	-0.107***	-0.104***
	(0.014)	(0.010)	(0.010)	(0.010)
R-squared	0.543	0.593	0.612	0.614
Observations	566,966	566,966	566,966	566,966
Geography	No	Yes	Yes	Yes
Built-up Density	No	No	Yes	Yes
Administrative Visibility	No	No	No	Yes

Notes: Robust standard errors clustered at the district level in parentheses. All models include district fixed effects and control for village-level (log) population and area. Geography includes distance to district headquarters and nearest town (imputed with missingness indicators), mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road. Administrative visibility controls include indicators for government primary schools, primary health centers, and PDS shops. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Dynamics of Exclusion: Robustness Across OLS and IV Strategies

	(1)	(2)	(3)	(4)
Share of SC	0.003	0.001	0.002	0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Share of ST	-0.042***	-0.036***	-0.044***	-0.041***
	(0.007)	(0.008)	(0.008)	(0.008)
Initial Reliability (2012)	-0.323***	-0.244***	-0.317***	-0.287***
	(0.014)	(0.064)	(0.043)	(0.046)
Method	OLS	IV	IV	IV
Geography	Yes	Yes	Yes	Yes
Δ Built-up Density	Yes	Yes	Yes	Yes
Visibility Controls	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
IV Diagnostics				
Instruments	–	Census 11 Access (1/0)	Census 11 Hours supply	Access (1/0) + Hours supply
KP rk Wald F	–	118.686	170.785	97.854
Hansen J p-value	–	–	–	0.195
Observations	566,966	529,786	523,462	523,451
R-squared	0.651			

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variable is Δ Probability Lit (2019–2012). All models include district fixed effects and control for village population, area, geography (includes distance to district headquarter and nearest town, mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road), and administrative visibility (includes indicators for government primary schools, primary health centers, and PDS shops). KP rk Wald F refers to the Kleibergen-Paap weak identification test statistic. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Structural Persistence and Mobility Traps: Sensitivity to Percentile-Based Poverty Definitions

	(1)	(2)	(3)
Threshold Used (*PrLit*)**:**	$< P_{10}$ **(0.12)**	$< P_{20}$ **(0.24)**	$< P_{30}$ **(0.36)**
Definition:	*(Extreme)*	*(Severe)*	*(Moderate)*
Panel A: Risk of Being Energy Poor (2012)			
Share of SC	-0.008	-0.021***	-0.032***
	(0.005)	(0.007)	(0.008)
Share of ST	0.116***	0.151***	0.156***
	(0.013)	(0.016)	(0.016)
Observations	566,966	566,966	566,966
R-squared	0.320	0.386	0.413
Panel B: Risk of Being Energy Poor (2019)			
Share of SC	-0.008	-0.021***	-0.023***
	(0.005)	(0.007)	(0.007)
Share of ST	0.076***	0.120***	0.149***
	(0.010)	(0.014)	(0.015)
Observations	566,966	566,966	566,966
R-squared	0.314	0.391	0.421
Panel C: Probability of Escaping Poverty (Conditional on Poor in 2012)			
Share of SC	-0.001	0.010	0.009
	(0.035)	(0.017)	(0.011)
Share of ST	-0.090***	-0.117***	-0.122***
	(0.019)	(0.017)	(0.018)
Observations	56,695	113,393	170,089
R-squared	0.417	0.490	0.511

Notes: Robust standard errors clustered at the district level in parentheses. All models include District Fixed Effects and village-level controls: log population, area, built-up density, geography (includes distance to district headquarter and nearest town, mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road), and administrative visibility (includes indicators for government primary schools, primary health centers, and PDS shops).
Panels A & B report the probability of a village falling below 2012 baseline percentile thresholds. Panel C restricts the sample to villages below the respective threshold in 2012 and tests the probability of crossing that threshold by 2019. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: The Gradient of Exclusion: Homogeneity and Enclave Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Var:	**Census-11 Access**	**Census-11 Supply**	**Reliability (2012)**	**Reliability (2019)**	**Energy Poor 2012**	**Energy Poor 2019**	**Escaped Poverty**
Metric:	*(1/0)*	*(Hours)*	*(PrLit)*	*(PrLit)*	$1(PrLit < P_{30})$	$1(PrLit < P_{30})$	*(1/0)*
Panel A: Scheduled Tribe (ST) Share *(Ref: < 30%)*							
30% – 50%	0.009*	0.124*	-0.013***	-0.020***	0.020***	0.018***	-0.030***
	(0.005)	(0.071)	(0.005)	(0.005)	(0.007)	(0.007)	(0.010)
50% – 70%	0.005	0.067	-0.038***	-0.042***	0.058***	0.046***	-0.045***
	(0.007)	(0.088)	(0.006)	(0.006)	(0.009)	(0.009)	(0.012)
70% – 90%	-0.022***	-0.268***	-0.070***	-0.074***	0.114***	0.100***	-0.087***
	(0.008)	(0.104)	(0.008)	(0.008)	(0.012)	(0.011)	(0.014)
90% – 100%	**-0.077*****	**-1.054*****	**-0.099*****	**-0.107*****	**0.166*****	**0.160*****	**-0.117*****
	(0.014)	(0.166)	(0.008)	(0.009)	(0.015)	(0.014)	(0.017)
Panel B: Scheduled Caste (SC) Share *(Ref: < 30%)*							
30% – 50%	0.002	0.037	0.007***	0.006***	-0.005*	-0.006***	0.011***
	(0.002)	(0.023)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
50% – 70%	0.003	0.068**	0.009***	0.006**	-0.005	-0.007**	-0.002
	(0.002)	(0.035)	(0.003)	(0.003)	(0.005)	(0.003)	(0.006)
70% – 90%	0.001	0.065	0.012***	0.005	-0.007	-0.006	-0.021
	(0.004)	(0.054)	(0.004)	(0.004)	(0.005)	(0.006)	(0.013)
90% – 100%	-0.011*	-0.099	0.017***	0.015***	-0.022***	-0.015*	-0.007
	(0.006)	(0.084)	(0.005)	(0.005)	(0.008)	(0.008)	(0.012)
Observations	551,365	544,356	566,967	566,967	566,967	566,967	170,089
R-squared	0.412	0.705	0.590	0.614	0.413	0.422	0.511

Notes: Robust standard errors clustered at the district level in parentheses. All models include District Fixed Effects and the full vector of village-level controls: log population, log area, built-up density, geography (includes distance to district headquarter and nearest town, mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road), and administrative visibility (includes indicators for government primary schools, primary health centers, and PDS shops).

Columns 5 and 6 report the probability of a village falling below the 30th percentile of the 2012 baseline reliability distribution ($PrLit < 0.36$). Column 7 restricts the sample to villages that were energy-poor in 2012 and tests the probability of escaping that status by 2019. *** p<0.01, ** p<0.05, * p<0.1.

Table A1: Political Representation and the Tribal Enclave Penalty

	(1)	(2)	(3)	(4)	(5)
Dependent Var:	**Reliability (2012)**	**Reliability (2019)**	**Energy Poor 2012**	**Energy Poor 2019**	**Escaped Poverty**
Metric:	$(PrLit)$	$(PrLit)$	$1(PrLit < P_{30})$	$1(PrLit < P_{30})$	*(1/0)*
Panel A: Scheduled Tribe (ST) Share *(Ref: < 30%)*					
30% – 50%	-0.010*	-0.016***	0.017**	0.017**	-0.038***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.011)
50% – 70%	-0.027***	-0.034***	0.047***	0.036***	-0.050***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.014)
70% – 90%	-0.050***	-0.061***	0.085***	0.076***	-0.089***
	(0.008)	(0.009)	(0.013)	(0.012)	(0.015)
90% – 100%	**-0.089*****	**-0.098*****	**0.146*****	**0.138*****	**-0.118*****
	(0.010)	(0.011)	(0.017)	(0.017)	(0.018)
Panel B: Interaction with ST-Reserved Constituency					
30–50% × ST Res.	-0.006	0.004	0.001	-0.012	0.038**
	(0.007)	(0.008)	(0.010)	(0.011)	(0.018)
50–70% × ST Res.	-0.014	0.004	0.015	0.001	0.030
	(0.009)	(0.010)	(0.013)	(0.016)	(0.023)
70–90% × ST Res.	-0.025**	-0.000	0.039**	0.017	0.026
	(0.011)	(0.012)	(0.017)	(0.018)	(0.025)
90–100% × ST Res.	-0.006	0.008	0.020	0.011	0.024
	(0.012)	(0.014)	(0.019)	(0.023)	(0.026)
ST Reserved Seat	-0.034***	-0.058***	0.041**	0.066***	-0.053**
	(0.011)	(0.014)	(0.016)	(0.020)	(0.021)
Observations	566,967	566,967	566,967	566,967	170,089
R-squared	0.591	0.616	0.414	0.424	0.511

Notes: Robust standard errors clustered at the district level in parentheses. All models include District Fixed Effects and the full vector of village-level controls: log population, log area, built-up density, geography (includes distance to district headquarter and nearest town, mean elevation, terrain ruggedness (TRI), forest land share, and the presence of an all-weather road), and administrative visibility (includes indicators for government primary schools, primary health centers, and PDS shops). All specifications control for Scheduled Caste (SC) share bins (coefficients not shown). Columns 3 and 4 report the probability of a village falling below the 30th percentile of the 2012 baseline reliability distribution ($PrLit < 0.36$). Column 5 restricts the sample to villages that were energy-poor in 2012 and tests the probability of escaping that status by 2019. *** p<0.01, ** p<0.05, * p<0.1.