

# Lines and Leviathan: Governance Capacity and its Role in Electricity Theft in India?



ISBN: 978-1-943295-26-5

**Bankim Samaddar**  
**Kausik Gangopadhyay**  
IIM Kozhikode  
(bankims03phdpt@iimk.ac.in)  
(kausik@iimk.ac.in)

*Using a state-year panel (2013–2023), we assess whether electricity-theft-proximate losses in India are driven more by governance capacity and political incentives than by prices or slow-moving socio-economics. Treating AT&C losses as the primary outcome and T&D as a comparator, two-way fixed-effects estimates show that opposition to the Centre raises losses, while fiscal capacity (Tax–GSDP), administrative reach (road length per capita), and an auditable customer mix (lagged industry share) reduce them. Real tariff is consistently insignificant; T&D additionally reflects scale (NSVA per capita). Results are robust to transforms, lags, and pooled/RE checks, motivating governance-first strategies for durable loss reduction.*

**Keywords:** Electricity theft, AT&C losses, Governance (state capacity), Political alignment, India—State-Year Panel

## 1. Introduction

Electricity theft—non-technical loss (NTL) through illegal connections, meter tampering, collusive under-billing, and chronic non-payment—remains a first-order constraint on India’s distribution utilities. It erodes cost recovery, inflates the ACS (Average Cost of Supply)–ARR (Average Revenue Realised) gap, and crowds out investment needed for reliability and the energy transition. Beyond the utility balance sheet, high theft undermines public trust and the equity of cross-subsidies, making accurate diagnosis of its determinants a policy imperative.

India’s last decade (2013–2023) provides a salient backdrop: standardized AT&C (Aggregate Technical & Commercial) loss accounting, targeted feeder/DT (Distribution Transformer) metering, smart-meter rollouts, and results-linked schemes attempted to discipline revenue cycles. Yet aggregate losses remain heterogeneous across states, and improvements have been uneven. This paper leverages that reform era as context—not as treatment—to examine whether year-to-year movements in theft-proximate outcomes are explained primarily by governance capacity and political incentives, or by prices/affordability and socio-economic structure.

A large comparative literature establishes that electricity theft is rooted in incentives and institutions (Smith, 2004). While credible detection and enforced sanctions cause non-technical losses to fall (Golden & Min, 2012), clientelism, weak supervision, and corruption blunt technical upgrades (Baskaran et al., 2015). Socio-economic stressors (low income, unemployment) and high tariffs can increase evasion incentives (Yurtseven, 2015; Jamil, 2013), while the customer mix (industrial/commercial vs. dispersed residential/agriculture) conditions detectability (Messinis & Hatzigiorgiou, 2018; Arevalo & Sarmiento, 2024; World Bank, 2001). In India, earlier work used T&D (Transmission & Distribution) losses as a proxy and highlighted governance correlates; qualitative studies documented collusion, local political interference, and uneven enforcement (Katiyar, 2005).

Two gaps motivate our study. First, despite policy emphasis on AT&C—the metric that embeds collection efficiency—most cross-state theft regressions still lean on T&D, which commingles engineering loss with theft. Second, India-wide panel evidence on political alignment with the Centre, state fiscal capacity, policing/corruption proxies, and administrative reach remains sparse for the reform decade. The literature seldom tests whether price variables (tariff) survive once we absorb unobserved state traits and national shocks, or whether socio-economic indicators (inequality, unemployment, urbanization) remain first-order after governance is accounted for.

We address these gaps with a pan-India, state-year panel (2013–2023) that (i) treats AT&C loss as the theft-proximate primary outcome and T&D loss as a comparator; (ii) foregrounds governance: Tax–GSDP (Gross State Domestic Product) as fiscal capacity, road length per capita as administrative reach, police and corruption proxies and political incentives: state–Centre alignment, election year; (iii) controls for prices/scale/structure; inflation-adjusted average tariff, NSVA (Net State Value Added) per capita, per capita availability of power, industry share in economy, unemployment, inequality, urbanization); and (iv) estimates two-way fixed-effects with state-clustered errors, complemented by pooled/RE checks and lagged/transform variants. To avoid mechanical overlap, we never pair collection efficiency (CE) with AT&C on the right-hand side; CE appears only in T&D robustness. Skewed level variables use log/asinh transforms; shares remain in levels. Because one state has negative capital employed in all years, we use asinh (capital) for the entire sample.

Data and methods are straightforward but disciplined. Loss measures are fractions in  $[0, 1]$ ; tariff and costs are deflated and some are intermittently interpolated (Gini, literacy, urbanization). The econometric backbone is state- and year-fixed effects

to absorb time-invariant heterogeneity and national shocks (including reform waves), with inference clustered by state. We probe timing with one-year lags (tariff, capacity, policing, corruption, roads, NSVA, industry share) and distributional robustness via  $\text{asinh}/\log$  transforms. A pooled (RE) read provides a between-plus-within descriptive foil.

Our results are stark. In the AT&C baseline (major states;  $N=177$ ), governance dominates: a state government in opposition to the Centre is associated with higher losses; fiscal capacity (Tax-GSDP), administrative reach (road length per capita), and an auditable customer mix (industry share) are each negatively related to losses. Unemployment is negative, consistent with a demand/composition channel. By contrast, Tariff is at best marginal. In the T&D baseline, governance signals persist (opposition  $\uparrow$ , road length  $\downarrow$ , industry share  $\downarrow$ ), but NSVA per capita turns positive and significant, highlighting the engineering/scale channel that T&D inevitably reflects.

This pattern suggests a division of labour between outcomes: AT&C is the better anchor for theft-proximate analysis (because it embeds collection discipline), whereas T&D is a useful comparator and engineering/scale effects surface more strongly. Policy-wise, the evidence points toward a two-track approach: tighten commercial governance (collections discipline, legal follow-through, depoliticized enforcement, data-driven inspection) to reduce AT&C, and pursue targeted network investments to compress T&D.

We also contribute methodologically. First, we demonstrate that sign-preserving transforms ( $\text{asinh}$ ) allow inclusion of states with negative capital employed without arbitrary offsets, and that governance inferences are transform-robust. Second, we show that dropping ACS (Average Cost of Supply) from the price block and retaining only Tariff avoids mechanical collinearity and leaves the governance core unaffected. Third, lag variants confirm that results are not timing-specific: governance effects persist with plausible delays, and tariff remains inert.

Finally, we situate the policy relevance. Every stolen kWh widens the ACS-ARR gap and consumes managerial bandwidth; conversely, better governance reduces losses and frees public resources for reliability and decarbonization. Our results suggest that theft reduction in India's reform era is less about "price pain" and more about credible enforcement, fiscal space, and coordination across levels of government. That emphasis—governance over price—can guide state-level prioritization, from strengthening revenue protection units and prosecution pipelines to ring-fencing subsidy flows and using smart-meter data for auditable action rather than dashboards alone.

## 2. Literature Review

Electricity theft is a persistent NTL that undermines the commercial viability of Indian distribution utilities and, by eroding cost recovery, constrains investments needed for reliable supply and the energy transition. Foundational comparative work establishes that theft spans illegal connections, meter tampering, billing irregularities, and non-payment; its incidence rises where institutions are weak, corruption is tolerated, and enforcement is uncertain (Smith, 2004; Depuru et al., 2011). India's accounting shift from T&D to AT&C—computed as one minus the product of billing and collection efficiencies—made commercial leakages salient and provides a theft-proximate outcome for our 2013–2023 state panel (Power Finance Corporation [PFC], 2009). Numerous reforms during the past decade of 2013–2023, primarily aimed at reduction of loss due to theft; so, reforms in this decade set the backdrop for the study.

### 2.1 Conceptual lenses: Incentives, Governance Capacity, and Social Norms

The political-economy literature treats theft as an equilibrium shaped by the expected gains from non-payment versus the expected costs of detection and sanction. Clientelist bargains, local political competition, and organizational collusion can sustain equilibria with high NTLs despite upgrades in hardware (Golden & Min, 2012; Sharma et al., 2016). Reviews emphasize that psycho-social factors—trust, perceived fairness, and employee behaviour—mediate technical fixes (Depuru et al., 2011). An explorative review synthesizing social and behavioural drivers argues that utilities must pair technical steps with attitudinal change among both customers and staff; corruption, literacy, risk perception, tariff salience, and collection discipline are repeatedly implicated (Saini, 2017). Together these strands motivate the central role for governance indicators—policing capacity, anti-corruption, fiscal capacity, and collection systems—in theft regressions.

### 2.2 Socio-Economic Determinants: Income, Affordability, Inequality, Structure, and Settlement

A consistent finding across developing regions such as South Asia and Africa is that affordability constraints, unemployment, and income dispersion shape theft incentives. Price-theft dynamics are clearest in time-series work from Pakistan: using cointegration and ECM/variance decomposition, Jamil (2013) shows that theft Granger-causes outages and contributes to rising tariffs, indicating a feedback loop where revenue leakage triggers capacity shortfalls and further price pressure. Household- and community-level studies similarly link high tariffs, poor quality, and corruption to pro-theft attitudes (Wabukala et al., 2023; Babar et al., 2022). In Ghana, a large urban–rural survey ranks higher electricity prices, poor quality, corruption, weak law enforcement, and a perceived lack of regulatory voice as the principal drivers; poverty, unemployment, and illiteracy matter but rank lower once price and quality are considered (Yakubu et al., 2018).

For India, machine-learning and econometric work demonstrates that socio-demographics and crime correlate with loss pockets: district-level models identify crime rate, literacy, income, urbanization, and per-capita use as strong predictors of non-technical loss (Razavi & Fleury, 2019). We extend this block by adding state-level inequality (Gini), largely absent in India-wide theft panels, drawing on evidence that inequality weakens compliance norms and interacts with governance in determining energy outcomes (Sarkodie & Adams, 2020). Socio-economic composition also conditions outcomes: higher

inequality (Gini) may weaken payment norms and intensify free-riding, particularly in urban commercial clusters where collusive under-billing is feasible (Sarkodie & Adams, 2020; Razavi & Fleury, 2019; Sharma et al., 2016).

We also include urbanization, industrial structure, and per-capita availability (a scarcity proxy), given evidence that dense commercial loads can either facilitate standardized billing or, in weak-governance settings, amplify collusive under-billing (Smith, 2004; Sharma et al., 2016).

### 2.3 Governance and Enforcement Capacity

Governance quality consistently conditions theft outcomes. State-level evidence for India links fiscal capacity, regulator strength, private participation, and collection discipline with lower theft (Gaur & Gupta, 2016). Case material from Rajasthan shows that vigilance, legal provisions, and metering upgrades underperform if field-level incentives and collusion persist (Katiyar, 2005). Parliamentary and program documents emphasize feeder/DT metering, ring-fencing, and AT&C computation rules (bounding collection efficiency at 100% to treat arrears separately) to localize losses and support enforcement (Standing Committee on Energy, 2016; PFC, 2009). Cross-country syntheses similarly connect higher police presence, credible inspections, and anti-corruption to lower NTLs (Antmann, 2009).

A further implication of this determinants-first view is that governance heterogeneity likely mediates price and socio-economic effects. In states with stronger fiscal capacity and tighter commercial routines (higher tax-GSDP; better ring-fencing and reconciliation), the same tariff need not translate into higher theft because detection probabilities and sanction credibility are higher (PFC, 2009; Standing Committee on Energy, 2016). Conversely, where collection and field supervision are weak, tariff increases may widen non-payment and encourage tampering (Depuru, Wang, & Devabhaktuni, 2011; Smith, 2004). Relatedly, using collection efficiency (CE) only in T&D models avoids mechanical overlap with AT&C while still capturing the revenue-side discipline emphasized in program design (PFC, 2009). Since theft and non-recovery inflate the ACS-ARR gap, curbing them frees fiscal space and managerial bandwidth for investments that underpin India's energy transition (Carr & Thomson, 2022; Gupta et al., 2025).

Finally, because AT&C embeds collection efficiency (CE), we only use CE as an explanatory variable when the dependent variable is T&D (not AT&C), avoiding mechanical overlap.

### 2.4 Politics and Selective Forbearance

Political incentives modulate enforcement. Electoral cycles coincide with higher measured losses in Indian administrative data, consistent with selective forbearance toward salient constituencies (Golden & Min, 2012; Min & Golden, 2014). Village and feeder studies document how patronage protects illegal connections or secures leniency in raids and billing (Katiyar, 2005). Consistent with this, quasi-experimental and billing-microdata studies show that ruling-party alignment facilitates relaxed enforcement and systematic under-billing for favoured constituencies—implying higher losses when the state government is aligned with the Centre (Baskaran et al., 2015; Mahadevan, 2024). These findings justify state-centre alignment and elections years as indicators (independent variables) in our panel as political one-upmanship often abets such crimes.

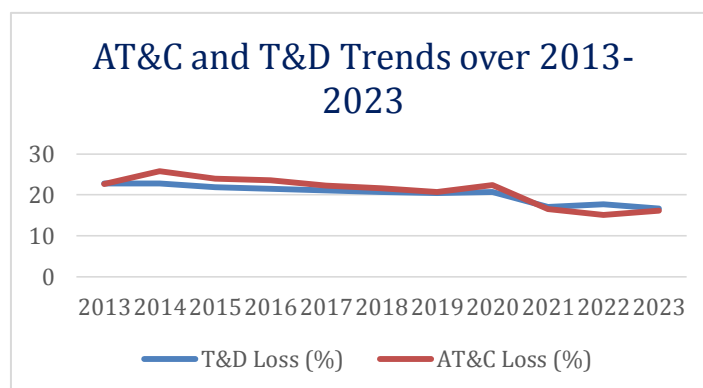
### 2.5 Technology and Analytics: Complements, not Substitutes

Technology has expanded rapidly in the 2010s and early 2020s: smart meters, SCADA (Supervisory Control and Data Acquisition), aerial-bunched cabling, HVDS (High Voltage Distribution System), and anomaly detection using AMI (Advanced Metering Infrastructure) data and neural networks (Shang et al., 2022; Jokar et al., 2016; McLaughlin et al., 2013). Yet evidence from India and abroad shows technology reduces measured losses only where institutions act on flags; otherwise, tampering and collusion adapt (Depuru et al., 2011; Sharma et al., 2016). A field-based synthesis of user acceptance finds that billing accuracy, local trust, and staff transition shape the realized gains from smart meters (Gupta et al., 2025). In short, technology raises the potential probability of detection; governance and legitimacy convert potential into realized deterrence.

### 2.6 Why 2013–2023? Reforms as Backdrop, not Treatment

The post-2013 policy environment standardized AT&C reporting, mandated energy accounting, and tied assistance to loss reduction and ACS-ARR convergence. Official releases in 2022–2023 highlight progress on these metrics, coinciding with smart-meter roll-outs and feeder audits (Press Information Bureau [PIB], 2022). We use reforms only to motivate the study window and measurement; common shocks are absorbed by year fixed effects. The analytical focus remains the relative salience of governance, socio-economic, and political variables in explaining theft.

**Graph1: AT&C and T&D loss Trend over 2013-2023**



## 2.7 Synthesis and Implications

Three themes recur. First, theft is governed by incentives and institutions: credible detection, anti-corruption, and fiscal capacity matter more than hardware alone. Second, socio-economic stress—income, unemployment, prices/affordability, and inequality—systematically shifts the payoff to evasion. Third, political timing and alignment mediate enforcement. By estimating pan-India models for 2013–2023 with AT&C (primary) and T&D (comparator), we quantify the comparative importance of governance, socio-economic, and political drivers—alongside prices—of theft. Because every avoided stolen kWh narrows ACS–ARR gaps and frees scarce public resources, credible theft mitigation generates co-benefits for India’s energy transition and climate goals.

## 3. Data & Methodology

### 3.1 Data and its Sources

We build a state panel for India over FY 2013-14 to FY2023-24 (2013–2023). The unit is the state-year; J&K and Ladakh are combined for consistency; Dadra & Nagar Haveli is combined with Daman & Diu post-merger. Altogether, we compiled data pertaining to 35 administrative units (States and Union Territories-UTs). However, the major-states subsample (population >2 crore as per population census 2011) is our focal study; while we use pooled panel of all observations. To the 2011 census based on the population cut-off criteria, the list of major state is as tabulated below (Table 1):

**Table 1**

Sr.No.	State/UT (2011 boundaries)	Population (Crore)
1	Uttar Pradesh	19.98
2	Maharashtra	11.24
3	Bihar	10.41
4	West Bengal	9.13
5	Andhra Pradesh (including Telangana)	8.46
6	Madhya Pradesh	7.26
7	Tamil Nadu	7.21
8	Rajasthan	6.85
9	Karnataka	6.11
10	Gujarat	6.04
11	Odisha	4.2
12	Kerala	3.34
13	Jharkhand	3.3
14	Assam	3.12
15	Punjab	2.77
16	Chhattisgarh	2.55
17	Haryana	2.54
18	Telangana*	3.5

**Note:** \* Although the state of Telangana was not a separate entity at the time of 2011 census but carved out of Andhra Pradesh later on 29th June 2014, the state government sources show a population of ~3.5 Crore inhabiting then in the area now under the state of Telangana. For our regression we have considered Telangana also as part of the major state group. Based on literature survey, we have identified 20 variables for our regression. The list of these variables, their sources and other details are given here in Table 2; expanded forms of the sources follow text

**Table 2**

Sr. No.	Variable	Unit	Remarks	Source
1	Tariff	Rupee/kwh	Inflation adjusted	CEA
2	ACS	Rupee/kwh	Inflation adjusted	PFC
3	Ruling Party	Category variable	1= same alliance in centre & state, 2= different alliance, 3= non-aligned, 4= President	ECI
4	T&D Loss	Nos.	Fraction (share) of total energy lost in transmission and distribution	RB

5	AT&C Loss	Nos.	Fraction (share) of total energy lost in transmission and distribution	PFC
6	Urbanisation	Nos.	Share of urban population in total	NCP
7	Per capita Corruption	Nos.	Total cases registered in the state divided by total population	NCRB
8	Unemployment	Nos.	Share of urban population in total	NSS, PLFS
9	Road Length	km	Per capita no. of kilometers of road-built year-wise	RBI
10	Net State Value Added by Economic activity (NSVA)	Rupees	Per capita NSVA in rupees (Constant prices)	RBI
11	Per capita power availability	kwh	Units of electricity available per person	RBI
12	Industry share	Nos.	Fraction (share) of industry in the total output of the economy (GSDP)	RBI
13	Road accident deaths	Nos.	Ns. of deaths per 100 accidents	NHAI
14	Per capita police personnel	Nos.	Population per policeman	BPRD
15	Tax-GDP ratio	Nos.	Share of own tax collection in total GDP of the state	RBI
16	Collection efficiency	Nos.	Share of revenue collection in total energy sold.	PFC
17	Capital employed	Rupee	Capital employed by state distribution utilities in a year	PFC
18	Major State	Category variable	Category variable; State with more than 2 Crores of population	
19	Inequality (Gini Co-efficient)	Nos.	Inequality score of a state year-wise. As year-wise data is available only for 2011 and 2017, so we have derived for other years by extrapolation	RBI
20	Literacy	Nos.	As share of literate population in total population year-wise. As the data is available for some of the years and not all, we have derived for others by extrapolation.	NSS, NSSO

### 3.1.1 Dependent Variables (DV)

- AT&C (Aggregate Technical & Commercial) loss: AT&C loss is the audited share of input energy not realized as revenue, combining technical loss, billing shortfall, and collection inefficiency. We use state-year AT&C (2013–2023) from official utility compilations as published by PFC in its annual report on “Performance of Distribution Utilities”. The data in percentage, we store it as fractions [0, 1] and treat AT&C as the primary theft-proximate outcome
- T&D (Transmission & Distribution) loss (comparator): T&D loss is the share of input energy not delivered to metered sales before billing/collection, thus mixing technical losses with theft. We assemble state-year T&D (2013–2023) from RBI (Reserve Bank of India), keep it as a comparator outcome to diagnose engineering/scale effects, and exclude collection-efficiency terms from the right-hand side.

Because AT&C mechanically embeds collection efficiency (CE), CE is not paired with AT&C as a regressor; CE appears only in first of the two T&D models to illuminate the revenue-side channel. We do so, also because of scope of comparison with previous panel study on theft with T&D as proxy, which used CE as an independent variable.

### 3.1.2 Independent Variables

#### • Prices and Finance Variable

- Tariff in Indian electricity sector is state-specific, being determined by state electricity regulatory commissions. Tariff order is issued by these commissions periodically and vary based on category-wise (domestic, commercial, agricultural, industrial and public utility services) as well as quantum (slab) of consumption: so, multi-slab. For our study, we have first derived category-wise tariff taking average of multi-slab tariffs and then averaged the category-wise tariffs to get the state-wise tariff for every year. The base data has been sourced from Annual General Review published by CEA (Central Electricity Authority).
- ACS (₹/kWh) and ACS-ARR gap data are also the inflation-adjusted average cost of supply. In robustness we use change in ACS-ARR to distinguish cost pressure from under-recovery. All ₹ variables (tariff, ACS, capital employed, income) are deflated to constant prices. Both the ACS and ACS-ARR gap have been sourced from PFC annual reports.

#### • Socio-Economic Variables

- Income is real NSVA (Net State Value Added by economic activity) per capita (₹/person).
- Unemployment is state-level unemployment rate (fraction), sourced from NSS-EUS (National Sample Survey – Employment Unemployment Survey) for 2013–15 and from PLFS thereafter.
- Inequality is a Gini score series at state level—available in 2011 and 2017 and extrapolated/interpolated for intervening years.
- Urbanisation is the urban population share (fraction, interpolated between Census and official updates).
- Industry share is the NSVA share of industry (manufacturing + utilities + construction) in total value added by economic activity, at constant price 2011-12.

6. Per-capita power availability (kWh/person) is an indicator of interest as we want to explore if 100% access of electricity to Indian homes impacted theft.
7. Literacy (share of literate) is a proxy to human capital/compliance norms. We have literacy figures for 2011 from census of India, for 2017-18 from 75th survey by NSO (National Statistical Office) on household social consumption and for 2023-24 from PLFS by NSSO (National Sample Survey Office). For intervening periods, we have derived by liner interpolation.

#### • Governance & Enforcement

Per-capita police personnel figures have been derived by inverting the “population per police personnel” figures available in BPRD (Bureau of Police Research & Development) annual reports.

Per-capita corruption is registered anti-corruption cases/complaints divided by population; both this set and Per-capita police personnel are entered as  $\text{asinh}$ . Zero-heavy rates (e.g., corruption cases per capita, police per 100k) are transformed using the inverse hyperbolic sine,  $\text{asinh}(\cdot)$ , which is linear near zero and log-like for large values, avoiding arbitrary ‘+1’ offsets while stabilizing skew.

Tax–GSDP (own-tax revenue as a share of GSDP) proxies fiscal/state capacity.

Road length per capita (km/person) captures not only the state “reach” but also the state capacity to execute projects.

The road-accident deaths per 100 accidents captures safety enforcement/output quality, both are aspects of governance. Together, these yield a multi-indicator view of governance capacity.

Collection efficiency (CE)—revenue collected divided by billed energy—enters only in T&D regressions.

Capital employed (₹, real) is the investment by state utilities in their respective infrastructure and we used as the same as a regressor being an indicator of governance.

#### • Political Economy Variables

Centre-State alignment follows the >6-months rule each financial year and is coded 1 (same party), 2 (alliance), 3 (opposition), 4 (President’s Rule). We operationalize this as dummies (same party, alliance, opposition and President’s Rule flagged separately in robustness).

Election year is a dummy for state assembly polls; incumbency change flags government turnover.

Among the variables described above, there are some which have not been used by any study on electricity theft in India; however, their significance as state capacity/governance has been established in other domains.

**Table 3**

Sr. No.	Variable description
1	Road length per capita
2	Police per capita
3	Deaths in accidents
4	Inequality measured in terms of Gini Score

**Table 4 Summary Statistics**

Variable	Obs	Mean	Std. dev.	Min	Max
State	0				
Year	385	2018	3.166393	2013	2023
TD_Loss	384	0.22597	0.100341	0.0224	0.546761
ATC_Loss	350	0.249092	0.13341	0.0358	0.7848
Tariff_real	383	8.29135	1.967162	3.59146	13.51221
ACS_real	335	7.847576	3.955408	4.463144	40.36749
ACS_ARR_ga~e	314	0.113071	0.150547	0.001621	0.82458
ACS_ARR_gap	321	1.133399	2.928189	0.01056	27.33014
Centre_Sta~t	385	2.376623	1.06359	1	4
Urban_share	385	0.421602	0.231192	0.1008	0.9989
Unemploye~e	384	0.058011	0.038082	0	0.32
Corruption~a	349	0.00443	0.004906	-0.00093	0.044118
Gini	286	0.269205	0.031463	0.205	0.374
Road_lengt~a	324	1.211563	1.864508	0.023632	17.30986
NSVA_per_c~l	355	113577.2	62305.06	22776	313973

Power_per~a	384	1551.414	2858.048	142.2	29667.8
Industry_s~e	354	0.137935	0.138563	-0.01549	0.767901
Deaths_per~t	376	38.89348	19.78036	6.2	102.9
Police_per~a	379	0.00348	0.002973	0.000679	0.01324
Collection~y	349	0.941956	0.078724	0.2927	1.1331
Tax_GDP_ra~o	334	0.080363	0.023071	0.02371	0.157508
Capital_em~l	366	41745.69	53360.09	-4294.51	205816.7
Literacy	385	0.81867	0.07535	0.6483	0.982
Election_y~y	384	0.171875	0.377764	0	1
Major_stat~y	385	0.514286	0.500446	0	1
state_id	420	18	10.11155	1	35

### 3.2 Methodology

#### 3.2.1 Design and Outcomes

We study the determinants of electricity theft—proximate losses using a state–year panel for 2013–2023. The primary outcome is AT&C loss (share in  $[0, 1]$ ) because it embeds collection efficiency, i.e., the locus of commercial governance. T&D loss (share in  $[0, 1]$ ) is used as a comparator outcome because it mixes technical losses with theft and thus captures engineering/scale pressures. Consistent with sector practice and to preserve interpretability, both outcomes enter in levels as bounded fractions; we do not fit fractional logit/QMLE.

Baseline estimators

Our benchmark is a two-way fixed-effects (FE) model with state and year effects, and standard errors clustered by state:

$$y_{st} = \beta'X_{st} + \alpha_s + \tau_t + \varepsilon_{st},$$

Where, includes governance, socio-economic, political, price, and structure controls, absorbs time-invariant state heterogeneity (institutions, baseline network topologies), and nets out national shocks (reform waves, macro cycles, fuel costs). Fixed effects are implemented via absorbed dummies; inference is state-clustered to allow arbitrary serial correlation within states. We prefer FE (over pooled/RE) given high intra-class correlation and the policy question of within-state movements.

#### Baseline Model 1: AT&C FE (Major States)

$$ATC_{it} = \alpha_i + \beta \cdot S_{it} + \Theta \cdot G_{it} + \Psi \cdot P_{it} + \gamma \cdot Pf_{it} + \varepsilon_{it}$$

Here, in model 1 AT&C loss is the proxy for theft. S, G, P and Pf respectively represent the socio-economic, governance, political economy and price-finance set of variables. Subscript denotes state and denotes year; variables with both subscripts together vary over state and time. Those with only are time-invariant

#### Baseline Model 2: T&D FE (Major States)

$$TD_{it} = \alpha_i + \beta \cdot S_{it} + \Theta \cdot G_{it} + \Psi \cdot P_{it} + \gamma \cdot Pf_{it} + \varepsilon_{it}$$

Here, in model 2 T&D loss is the proxy for theft; other notations are same as those as in model 1.

Both the baseline models include state fixed effects (absorbing time-invariant traits—geography, legacy institutions) and year fixed effects (absorbing national shocks and common reforms). Regressors are grouped as:

Prices/finances: real tariff; real ACS (and ACS–ARR in robustness).

Socio-economics: per capita NSVA, unemployment, urbanisation, industry share, Gini, per capita power availability and literacy.

Governance: police per 100k, road length per capita and corruption per capita, tax–GSDP (Gross State Domestic Product); road-deaths per 100 accidents; CE (only when T&D is Dependent Variable) and asinh (Capital employed).

Political economy: alignment dummies; election year.

**Variable Treatment and Transformations:** We follow a disciplined transformation scheme to stabilize skew while retaining policy meaning. We store percentages as fractions, log-transform positive continuous variables, use asinh for zero-heavy rates. We use Logs (ln) for strictly positive scale variables: NSVA per capita and per capita power availability, and asinh(·) (sign-preserving, log-like) for zero-heavy or potentially negative capacity/enforcement proxies: capital employed, police per capita, corruption per capita, road length per capita. (Three non-major states: Arunachal Pradesh, Nagaland and Mizoram

exhibit negative capital employed in all years; asinh keeps the state in-sample without arbitrary offsets.).

We use levels for bounded shares: AT&C, T&D, Tax-GSDP, industry share, unemployment, urban share, Gini, and collection efficiency (CE capped at 1). The political variables: Centre–state alignment is coded categorically; value 3 denotes opposition to the Centre (our forbearance proxy). Election year is a 0/1 indicator.

To avoid mechanical overlap and collinearity, AT&C models never include CE on the right-hand side, and Tariff\_real is not co-included with ACS\_real or ACC–ARR gap in the baseline regression but in some robustness models.

To mitigate simultaneity, tariff, ACS, policing, corruption, and capital employed we use both without lag and lagged one year in the core models, with contemporary variants shown in robustness. We have used financial year (FY) 2013-14 as year 2013, FY 2014-15 as 2014 and so on. For the price/finance variables and robustness we treat the variable Tariff (₹/kWh) as the policy-legible price lever in the baseline. Two alternative framings check sensitivity: (i) adding ACS (₹/kWh) beside tariff, and (ii) replacing ACS with ACC–ARR gap (level). These are presented as robustness, not as headline drivers, since gap metrics are composite outcomes endogenous to losses and tariff-setting.

### Interpretation

Coefficients are within-state partial correlations after purging time-invariant state traits and national shocks. Our identification is reduced-form; we therefore emphasize sign, stability, and policy plausibility across robustness exercises rather than structural magnitudes.

Robustness strategy- for AT&C our primary Dependent Variable: i) All state fixed effect regression; (ii) Baseline with random effect iii) All State with random effect iv) Baseline with ACS (iv) lagged tariff/ACS/police/corruption/capital; (v) Baseline with transformed variables (vi) Baseline with lagged variables (vii) Baseline with transformed and lagged variable (viii) Baseline with year dummy (ix) Baseline with ACS-ARR gap x. Coefficients from fractional models are presented as marginal effects at representative values to aid interpretation.

This design centres the comparative significance of governance, socio-economic, and political variables—across major states and the full panel—and explicitly tests novel covariates (Gini; road-safety outcomes; road length per capita) alongside classics from the theft literature.

## 4. Results

- **Baseline results:** AT&C (major states, FE with year effects)

The within-state fixed-effects (FE) model for AT&C losses ( $N \approx 177$ , within  $R^2 \approx 0.52$ ) indicates that governance and political economy dominate year-to-year movements in loss outcomes, while prices are not a first-order driver once unobserved heterogeneity and common shocks are absorbed. The headline result is a political-alignment effect: when a state government is in opposition to the Centre, AT&C losses are higher, with a positive and statistically significant coefficient on the opposition category. This pattern is stable across specifications and directly supports a “political forbearance/coordination” channel—i.e., weaker administrative cooperation on billing enforcement, raids/recoveries, and prosecution, and slower movement on subsidy reimbursement workflows when Centre–state political incentives differ.

A second, equally robust finding is the role of state fiscal capacity. The Tax–GSDP ratio enters negatively and significantly: higher own-revenue mobilization is associated with lower AT&C losses. Substantively, greater fiscal room allows utilities and their line departments to sustain revenue operations—smart-meter MDM, feeder/distribution-transformer audits, data-driven inspections, legal follow-through, and working-capital support—without slipping into ad-hoc forbearance during cash stress.

Third, administrative reach and auditable customer mix matter. Road length per capita (a practical reach proxy) is negative and significant, indicating that physical accessibility improves inspection density, reduces frictions with local policing/courts, and increases the perceived probability of detection. Industry share is negative and significant, consistent with industrial/commercial customers being (i) largely three-phase and tightly metered, (ii) larger bills that attract attention, and (iii) embedded in LC/bank-guarantee arrangements that compress arrears tolerance. Together these coefficients narrate an operational mechanism: better reach and a more auditable load mix reduce opportunities for pilferage and collusive under-billing.

Among socio-economic controls, unemployment is negative and statistically significant in the baseline, a finding we interpret as a demand/composition effect: weaker activity compresses both legitimate consumption and theft opportunities, thus reducing measured AT&C. Deaths per 100 road accidents also enters negative at conventional levels; we treat this as an additional composition/intensity proxy rather than a causal safety effect per se. In contrast, tariff is insignificant to marginally positive (borderline at best). Once state FE and common year effects soak up national shocks (including reform waves and macro cycles), tariff does not explain within-state swings in AT&C. Likewise, NSVA per capita, power per capita, police per capita, capital employed, urban share, Gini, election year, and (in the baseline with only tariff) corruption per capita are imprecise.

- **Baseline Results: T&D** (major states, FE with year effects)

For T&D losses ( $N \approx 177$ , within  $R^2 \approx 0.43$ ), we again observe a strong governance imprint but a more evident engineering/scale channel. Tariff\_real is insignificant, reinforcing the limited role of price in explaining within-state variation



once FE are included. The opposition-to-Centre category remains positive and significant, indicating that alignment matters even for an outcome that mixes technical and non-technical components.

Two structural variables are central. First, NSVA per capita is positive and significant: as economies scale, measured T&D rises unless technical investments (HVDS, reconductoring, capacitor banks, feeder segregation, DT metering) and energy-accounting upgrades keep pace. This is consistent with T&D bundling technical losses with theft. Second, industry share is negative and significant, again indicating that a more auditable load mix (industrial/commercial customers) lowers aggregate losses. Road length per capita is negative and significant—consistent with better last-mile reach enabling more effective network maintenance and metering/inspection.

Comparing baselines, the political and reach/mix signals recur in both AT&C and T&D, while scale/cost shows up in T&D (through NSVA per capita) but not in AT&C—exactly the separation we would expect if AT&C is a more commercial-governance outcome and T&D additionally reflects engineering losses.

#### • **Robustness: i) Model Re-Framing of the Price/Cost Block**

We ran three key alternatives to ensure the price/cost treatment does not drive the governance findings

**First**, by adding ACS (Tariff + ACS together). Neither price nor cost becomes significant; all core governance and capacity results (opposition ↑; Tax–GSDP, road length, industry share ↓) are unaffected. This supports our decision to drop ACS from the base to avoid collinearity and over-controlling. Second, by replacing Tariff with ACC–ARR gap (in levels). The gap is typically insignificant in AT&C FE; governance coefficients remain stable. Third, by adding CE in T&D models only. Where examined, collection efficiency enters the T&D equation (not AT&C) by construction; signs can be counter-intuitive in pooled settings (joint determination/measurement). We therefore keep CE out of the AT&C regressions and interpret any CE–T&D links with caution.

Across models, the governance core is invariant; tariff/ACS are not decisive in explaining within-state AT&C variation.

#### ii) Distributional and timing checks

First, with transforms (asinh/log); we applied sign-preserving asinh to zero-heavy or negative-possible variables (capital employed, police per capita, corruption per capita, road length per capita) and logs to positive scale variables (NSVA per capita, power per capita). The opposition and Tax–GSDP findings are unchanged; road length sometimes trades significance with urban share (reflecting overlapping “reach/structure” content), corruption per capita turns negative and significant when transformed (consistent with detection/reporting), and unemployment attenuates slightly. The narrative—governance over price/scale—remains intact.

**Second**, with Lags (1-year); we lagged Tariff, industry share, Tax–GSDP, road length, police, corruption, NSVA, and power per capita. Governance effects persist with plausible delays: lagged Tax–GSDP and lagged road length are again negative, opposition remains positive, and lagged tariff stays insignificant. In some lagged/transform variants, urban share and log (power per capita) turn negative, suggestive of formalization as supply/settlement density rises. Importantly, leads of political alignment are null where tested, consistent with the absence of pre-trends driving the political result.

#### iii) Sample and estimator:

All-states FE (states + UTs). The governance story replicates: opposition ↑ AT&C; Tax–GSDP and road length ↓. Differences include weaker unemployment, and industry share/corruption losing precision (heterogeneity/measurement). Tariff may appear marginally positive in the larger sample, consistent with affordability pressures in select smaller jurisdictions; however, this is not robust once FE and common shocks tighten.

Pooled/RE (all states). Random-effects (or pooled with year effects) is a useful descriptive foil. The opposition and Tax–GSDP results survive. Variables driven by persistent between-state differences tend to look stronger in RE and weaker in FE; conversely, variables explaining within-state movement (our focus) tighten in FE. We regard RE as supportive but not decisive; FE remains the inferential benchmark.

#### • **Model diagnostics**

Across FE models, the Hausman logic (high  $\rho$ , significant FE tests) supports the fixed-effects framework. Within  $R^2$  values are stable and healthy ( $\approx 0.5$  for AT&C,  $\approx 0.4$ – $0.45$  for T&D). Results are insensitive to removing ACS from the price block, to distributional transforms, and to introducing 1-year lags. In sum, governance variables (political alignment, fiscal capacity, reach, auditable mix) consistently explain AT&C variation; Tariff\_real does not, and T&D appropriately reflects additional engineering/scale features.

#### **Some selected Regression Models and their Salient Findings: with AT&C loss as Dependent Variable**

Sr. No.	Model	Price-finance	Political	Governance/State Capacity	Socio-economic
1	ATC FE baseline (major state)	Tariff: (+) *	Opposition: (+) ***	Tax–GSDP: (–) ***; Road length pc: (–) ***; Road-deaths: (–) **	Industry share: (–) **; Unemployment: (–) **
2	ATC All State FE (robustness)	Tariff: n.s.;	Opposition: (+) **	Tax–GSDP: (–) ***; Road length: (–) **; Road-deaths: (–) *	Unemployment: (–) **
3	Baseline model with selected transformed variables (robustness)	Tariff: n.s.	Opposition: (+) ***	asinh_corruption: (–) **	Industry share: (–) *; Urban share: (–) **; Unemployment: (–) *
4	Baseline with selected lagged variables (robustness)	Tariff: n.s.	Opposition: (+) ***; Alliance: (+) **	L1 Road length: (–) *; L1 NSVA: (+) *; Deaths: (–) *; L1 Tax-GSDP: (–) ***	Industry share: (–) *; Urban share: (–) *

5	Baseline with RE instead of FE (robustness)	Tariff: (-) *	Opposition: n.s.	Tax-GSDP: (-)***; Capital Employed: (+)***; Corruption:(+) *; Road length: (-) **;	Inequality: (+) ***; Urban share: (-) ***; NSVA: (-)***
6	Baseline with selected transformed and lagged variables(robustness)	Tariff: n.s.	Opposition:(-) ***; Alliance: (-)***	asinh_road: (-) *; L1.Tax-GSDP: (-)***; L1.asinh_capital employed: (+)*	L1.Industry share: (-) *; L1. ln_power availability: (-) ***; Urban share: (-) **; L1.ln_NSVA: (+) *

Table 6 Some Selected Regression models and their Salient Findings: with T&amp;D Loss as Dependent Variable

Sr. No.	Model	Price-finance	Political	Governance/State Capacity	Socio-economic
1	TD FE baseline (major state)	Tariff: n.s.	Opposition: (+) **	Tax-GSDP: (-) ***; Road length pc: (-) **; Road-deaths: (-) **	Industry share:(-) **; Unemployment: (-) **; NSVA: (+) ***; Inequality: (+) *
2	TD Baseline with ACS and Collection Efficiency added (robustness)	Tariff: n.s; Collection Efficiency: (+) **	Opposition: (+) **	capital employed: (+) *	Unemployment: (-) **; NSVA: (+) **; Inequality: (+) **

**Notations used:** - n.s.: Not Significant; \*, \*\* and \*\*\* are significance respectively at 1%, 5% and 10% level; (+) & (-) are signs of the coefficients.

## 5. Discussion

### • Interpreting the AT&C Baseline

The AT&C baseline identifies a commercial-governance mechanism rather than a price mechanism. First, the persistent opposition effect points to political forbearance and coordination frictions: when Centre-state alignment is low, the political cost of strict enforcement (raids, disconnections, prosecution) rises and bureaucratic cooperation across levels weakens. This one-line coefficient captures a broad set of frictions—field-level discretion, local patronage, slower subsidy reconciliation—that ultimately attenuate revenue discipline. Second, tax-GSDP is a strong negative predictor, which we read as capacity to enforce: own-revenue-rich states can fund the mundane but critical back-office and field operations that keep AT&C low, including MDM (Meter Data Management) upkeep, feeder/DT metering, energy audits, and recovery drives. Third, road reach and industry share—operational proxies for inspector access and auditable loads—are negative, showing that detection probability and customer-mix materially shape NTL.

### • Interpreting the T&D Baseline

T&D is a composite of engineering loss plus theft, and the estimates reflect that mix. The opposition effect stays positive, implying that governance permeates both the commercial and technical sides—coordination matters for energy accounting and loss-reduction drives as much as it does for collections. The distinctive feature of T&D relative to AT&C is the scale channel: NSVA per capita is positive, meaning that as economies grow, measured T&D rises unless the network is upgraded alongside (reconductoring, capacitor banks, HVDS, feeder segregation) and energy accounting is tightened (DT metering, feeder audits). The continued negativity of industry share and road length is consistent with an auditable mix and reach lowering even the engineering part of losses (through more frequent inspection, faster fault response, better load management). Tariff remains unimportant, suggesting that even when theft is bundled with technical losses, retail price variation does not systematically press on the loss ratio within states after FE controls.

### • AT&C vs. T&D as Theft Measures

Which metric should anchor a study explicitly about theft? Our evidence supports AT&C as the primary outcome and T&D as a structured robustness. AT&C, by construction, incorporates collection efficiency—exactly where governance and political incentives bite: under-billing, arrears tolerance, negotiated disconnections, and strategic non-enforcement. In the estimates, AT&C responds cleanly to opposition, Tax-GSDP, road reach, and industry share, while Tariff\_real remains marginal.

T&D is not discarded; it is informative in a different way. Its positive association with NSVA per capita flags engineering/scale pressures: as systems get larger and more complex, technical losses and energy-accounting gaps re-emerge unless the network is modernised and the utility's OT/IT stack is maintained. The fact that governance signals (opposition ↑; road length/industry share ↓) persist in T&D confirms that political economy does influence even the engineering composite—but the magnitude and precision are diluted by technical components. Using both outcomes together helps attribute movements correctly: AT&C tracks changes in commercial governance; T&D catches where technical upgrading must accompany enforcement to sustain loss reduction.

### • Why governance Dominates Prices and Socio-Economics

The reform decade (2013–2023) is instructive because **many national shocks were common**—from standardized AT&C accounting to large-scale feeder/DT metering and the first smart-meter waves—and are absorbed by year fixed effects. Within that environment, the data show that **who enforces and how well** matters more than **what the retail price is**. There are three reasons.

First, **selective forbearance and coordination** are structurally important in a federal system with layered political incentives. Opposed states face higher political costs for strict enforcement and fewer administrative complements from the

Centre (and vice-versa). The robust, positive **opposition** coefficient across AT&C and T&D is hard to mimic with engineering stories; it is quintessentially political-administrative.

Second, **capacity is cumulative**. **Tax–GSDP** and **road length** unpack different parts of that capacity: fiscal space to finance sustained operations, and physical reach to keep inspectors/teams present where loss pockets persist. These are not quick fixes; they are indicators of a state's ability to maintain **credible threat of detection** and **follow-through** on recoveries, month after month.

Third, **customer mix matters**. Moving towards **industrial/commercial shares**, with better metering and contractual arrangements, compresses the feasible space for theft even if volume grows. This is not a “rich vs. poor” effect; it is a **contracting and auditability** effect.

Classical socio-economic controls—**inequality, literacy, urban share**—are slower moving and often collinear with governance proxies; in FE they have less to say about **within-state** year-to-year swings. **Unemployment's** negative association (when present) reinforces the **demand/composition** mechanism rather than a normative compliance story. Finally, **tariff** does not move AT&C once FE and governance are in place, indicating that affordability-driven theft, while plausible in theory, is not the dominant margin in the data after reforms' common shocks and state heterogeneity are purged.

#### • **Political Forbearance: A Concise Note**

Because **opposition to the Centre** consistently raises losses across outcomes and variants, the data are consistent with **political forbearance**: selective under-enforcement and slower coordination when political alignment is low. We do not claim intent; these are reduced-form associations. But the sign's persistence and stability across specifications elevate political incentives to a **first-order determinant** of theft-related losses in India's distribution sector.

#### • **Policy Implications**

The separation between AT&C and T&D determinants maps naturally to a **two-track strategy**. For AT&C, interventions should prioritize **commercial governance**: depoliticized enforcement, revenue-protection units with prosecution pipelines, ring-fenced and timely subsidy flows, analytics that trigger **auditable action** (not just dashboards), and sustained MDM/MDAS operations. For T&D, focus on **technical upgrades and energy accounting**: HVDS, reconductoring, capacitor banks, feeder segregation, DT metering and audits, with dedicated O&M budgets and uptime SLAs for the IT/OT stack. Because **alignment** appears to matter, formal **Centre–state coordination platforms** that insulate enforcement from political cycles can pay off. Because **Tax–GSDP** correlates with success, fiscal instruments that bridge working-capital gaps (contingent credit lines, escrow backing) can relieve commercial leniency pressures.

#### • **Methodological Takeaways**

Methodologically, two choices mattered. First, using **AT&C as the primary DV** (and T&D as comparator) sharpened attribution to **governance** vs. **engineering** channels. Second, distribution-aware transforms—especially **asinh** for variables that can be zero or negative (capital employed)—allowed us to keep all states in-sample without arbitrary offsets, and the **governance coefficients were transform-robust**. Across a decade marked by reforms and common national shocks, India's cross-state differences in theft-proximate outcomes are explained far more by **governance capacity and political alignment** than by **prices** or slow-moving socio-economics. **AT&C** is the right anchor for theft analysis; **T&D** is the right comparator for technical load. The data argue for **credible enforcement and administrative reach**, complemented—not replaced—by engineering upgrades.

## 6. Conclusion

This paper studies determinants of electricity-theft–proximate losses in India during 2013–2023—a decade of intensified distribution reforms and better loss accounting. Using a state–year panel with two-way fixed effects, we separate Aggregate Technical & Commercial (AT&C) loss—embedding collection discipline—from T&D loss, which mixes engineering loss with theft.

Three results stand out. First, governance and politics dominate: AT&C (and, to a lesser extent, T&D) losses are higher when a state government is in opposition to the Centre, consistent with selective forbearance and weaker inter-governmental coordination. Second, state capacity matters: higher Tax–GSDP (fiscal space) and greater administrative reach (road length per capita) are associated with lower losses, while a more auditable customer mix (lagged industry share) also reduces losses. Third, prices are not the lever: after absorbing unobserved state traits and national shocks, real tariffs do not explain within-state variation in losses; for T&D, scale/engineering pressures (NSVA per capita) surface instead.

Findings are robust to alternative price/cost framings (adding ACS or substituting the ACS–ARR gap), distribution-aware transforms (asinh/log for skewed variables), one-year lags to mitigate simultaneity, broader samples (all states and UTs), and pooled/random-effects estimators. The stability of political-alignment and capacity coefficients supports a governance-centric interpretation of theft in the reform era.

Policy follows. For AT&C, returns lie in commercial governance: depoliticised enforcement, revenue-protection units with prosecution pipelines, timely subsidy reconciliation, and analytics that trigger auditable action—not dashboards alone. For T&D, payoffs are engineering: HVDS, reconductoring, capacitor banks, feeder/DT metering and audits, and funded IT/OT upkeep. Because political alignment shapes outcomes, formal Centre–state coordination that insulates enforcement from

electoral cycles is prudent; because fiscal space predicts success, financial instruments that stabilise working capital can reduce tolerance for arrears.

## 7. References

1. Arévalo, J. & Sarmiento, P. (2024). Detection of Non-Technical Losses in Special Customers with Telemetry, Based on Artificial Intelligence. <https://doi.org/10.3390/engproc2024077029>
2. Antmann, P. (2009). Reducing technical and non-technical losses in the power sector. World Bank. <https://documents1.worldbank.org/curated/en/829751468326689826/pdf/926390WP0Box3800in0the0power0sector.pdf> World Bank
3. Baskaran, T., Min, B., & Uppal, Y. (2015). Election cycles & electricity provision. [https://yuppal.people.yasu.edu/electoral\\_cycles\\_paper.pdf](https://yuppal.people.yasu.edu/electoral_cycles_paper.pdf) yuppal.people.yasu.edu
4. Carr, D., & Thomson, M. (2022). Non-Technical Electricity Losses. *Energies*, 15(6), 2218. <https://www.mdpi.com/1996-1073/15/6/2218> MDPI
5. Depuru, S. S. R., Wang, L., & Devabhaktuni, V. (2011). Electricity theft: Overview, issues, prevention and a smart meter based approach. *Energy Policy*, 39(2), 1007–1015. <https://www.sciencedirect.com/science/article/abs/pii/S0301421510007621> leitner.yale.edu
6. Gaur, V., & Gupta, E. (2016). The determinants of electricity theft: An empirical analysis of Indian states. *Energy Policy*, 93, 127–136. <https://www.isid.ac.in/~cecf2/publication/the-determinants-of-electricity-theft-an-empirical-analysis-of-indian-states/> isid.ac.in
7. Golden, M., & Min, B. (2012). Theft and loss in Indian electricity. (Working paper / AJPS context). [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2310112](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2310112) IDEAS/RePEc
8. Jamil, F. (2013). Electricity shortage, price and electricity theft nexus. <https://www.jstor.org/stable/24398408> JSTOR
9. Katiyar, S. K. (2005). Political economy of electricity theft in rural areas: A case study from Rajasthan. *Economic & Political Weekly*, 40(7), 644–648. <https://www.epw.in/journal/2005/07/special-articles/political-economy-electricity-theft-rural-areas.html> epw.in
10. Messinis, G. & Hatziaargyriou, N. (2018). Review of non-technical loss detection methods. <https://doi.org/10.1016/j.epr.2018.01.005>.
11. Min, B. (2014). Electoral cycles in electricity losses in India. *Energy Policy*, 65, 619–625. <https://ideas.repec.org/a/eee/enepol/v65y2014icp619-625.html> IDEAS/RePEc
12. Power Finance Corporation (2009). Methodology for establishing baseline AT&C losses (R-APDRP). [https://www.pfcindia.co.in/ensite/DocumentRepository/ckfinder/files/GoI\\_Initiatives/R-APDRP/Methodology\\_for\\_Baseline\\_AT%26C\\_Losses.pdf](https://www.pfcindia.co.in/ensite/DocumentRepository/ckfinder/files/GoI_Initiatives/R-APDRP/Methodology_for_Baseline_AT%26C_Losses.pdf) indiabudget.gov.in
13. Razavi, S., & Fleury, E. (2019). Socio-economic predictors of electricity theft in developing countries: An Indian case study. *Energy for Sustainable Development*, 49, 1–10. [https://www.researchgate.net/publication/332122034\\_Socio-economic\\_predictors\\_of\\_electricity\\_theft\\_in\\_developing\\_countries\\_An\\_Indian\\_case\\_study](https://www.researchgate.net/publication/332122034_Socio-economic_predictors_of_electricity_theft_in_developing_countries_An_Indian_case_study) ResearchGate
14. Smith, T. B. (2004). Electricity theft: A comparative analysis. *Energy Policy*, 32(18), 2067–2076. <https://www.sciencedirect.com/science/article/abs/pii/S0301421503002917> iitk.ac.in
15. Wabukala, B. M., et al. (2023). Impact of household electricity theft and unaffordability on electricity security: Uganda. *Energy Policy*, 173, 113411. <https://doi.org/10.1016/j.enpol.2022.113411>.
16. Yurtseven, Caglar (2015). The causes of electricity theft: An econometric analysis of the case of Turkey. <https://doi.org/10.1016/j.jup.2015.06.008>