The Price of Power: Costs of Political Corruption in Indian Electricity

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- Understudied: political capture of large public utilities
    - Electricity and water - state operated, and not managed by politicians
- Welfare implications of political capture unclear - who is targeted?
    - Are the benefits to targeted consumers justified by efficiency losses?

Are public utilities vulnerable to political capture?

West Bengal power sector illustrates the difficulties of power reform

Moneylife Digital Team
09 June 2016

The Telegraph India
Tuesday, July 17, 2018

Home > Jharkhand
Power theft jolt: Rs 3.9cr

No hike of power tariff in Bengal

Source : Business Standard
By : Rajat Roy
Last Updated: Wed, Dec 05, 2012 03:50 hrs

The Washington Post
Democracy Dies in Darkness

Asia & Pacific
Power thieves prosper in India's patronage-based democracy

The Telegraph India
Tuesday, July 17, 2018

Home > West Bengal
Power officials assaulted at eatery

WBSEDCL suffered Rs 175.85-cr revenue loss in FY16: CAG report

Press Trust of India | Kolkata
Last Updated at March 8, 2018 18:35 IST

The Economic Times

Power utilities should be freed from political interference:West Bengal

Research Question

1. **How does alignment with the ruling party affect the political capture of a large public utility?**

2. **What are the welfare implications of political patronage?**

Preview of Results

- **Close election RD**: causal evidence of patronage towards constituencies aligned with the ruling party

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  - *Actual* electricity consumption higher (satellite nighttime lights)
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  - Manipulate consumption data to lower bills
- **Welfare Consequences of Patronage**
  - Loss is producer surplus more than double gain in consumer surplus
  - Deadweight loss → enough to power 3.7 million rural households
  - Producer loss → lower quality of electricity

Contributions

Causally infer direction of political patronage and quantify losses

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- **Evidence of Political Patronage in Public Sector Enterprise**
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- **Demand estimation**
  - Develop method of demand estimation under data manipulation
  - More robust elasticities: micro-data important

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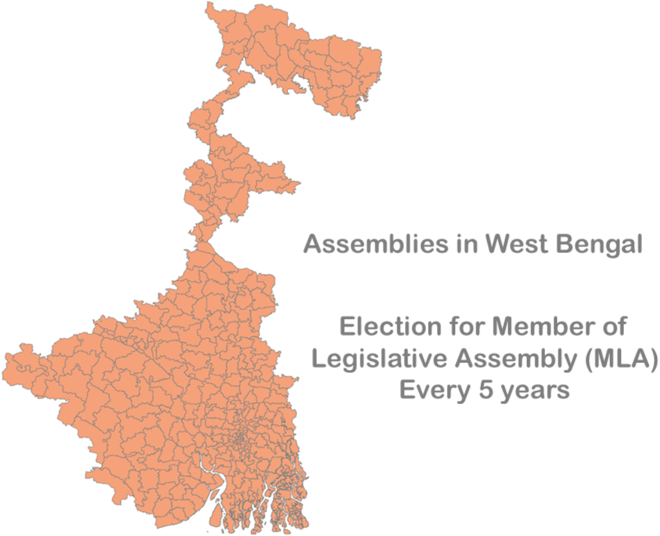
- **Evidence of Political Patronage in Public Sector Enterprise**
  - Mechanisms of corruption at micro-level
- **Demand estimation**
  - Develop method of demand estimation under data manipulation
  - More robust elasticities: micro-data important
- **Unintended Consequences of Patronage**
  - Large efficiency losses due to poor targeting

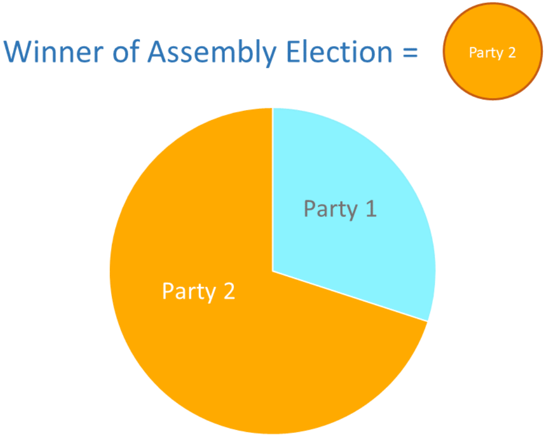
Data and Descriptives

- **Confidential billing data and administrative records:**
  - Universe of accounts (17 mill) of large state utility in India
  - Quarterly, 2011-2017
  - Consumer categories: residential, commercial
- **Satellite DMSP-OLS nighttime lights data 2000-2017**
  - Proxy for electricity: Burlig & Preonas 2016, Min & Golden 2014
- **Tariff data (2009-2017)**: updated every 1-2 years
- **State elections data (2006, 2011, 2016):** vote shares by party
- **Indian Census 2011** - Village level characteristics

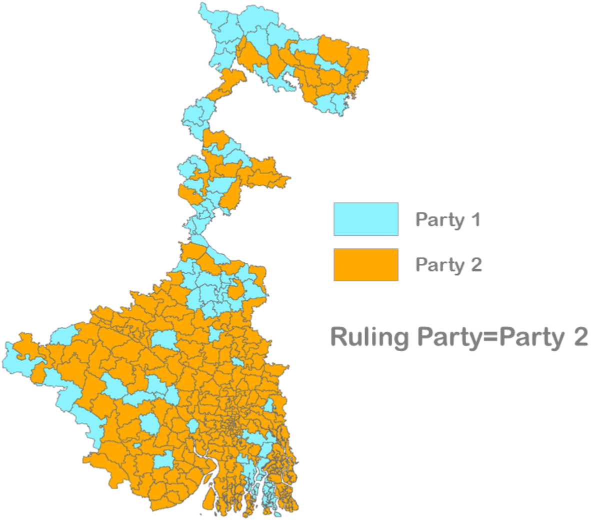
State Elections in India



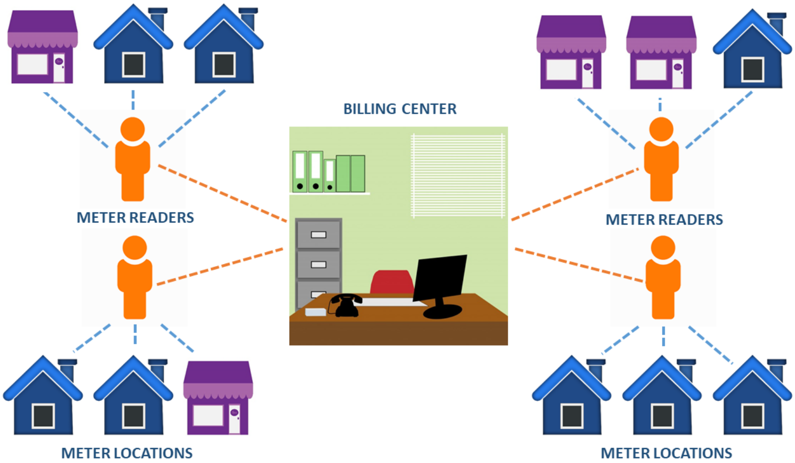
Assembly Election - Majority Party



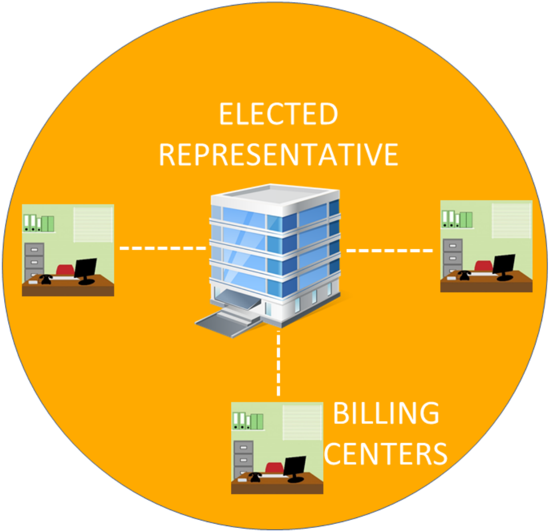
State Election Winner - Simple Majority of Assemblies



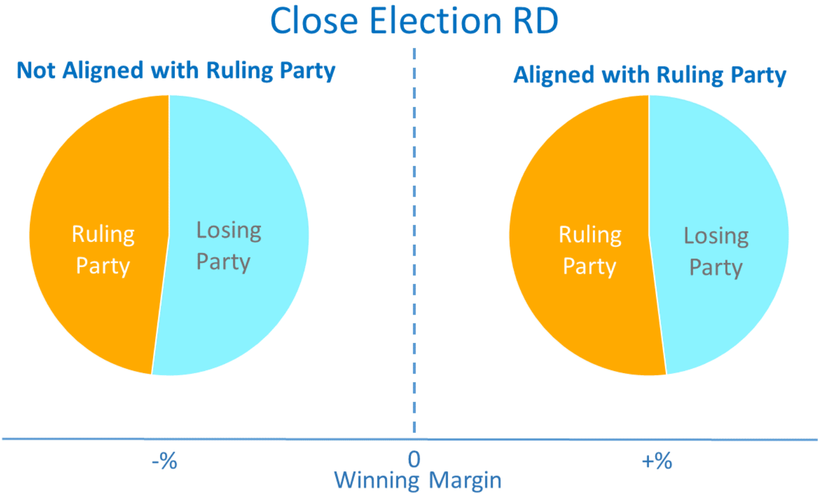
Electricity Billing Practices



Electricity Billing Practices - Constituency level



Close Elections at Assembly Level



Identification Strategy - Close Election RD

- Close election RD: Causal impact of being in winning constituencies

  Summary Statistics

- Optimal bandwidth and binning procedure (Calonico et al. 2014)

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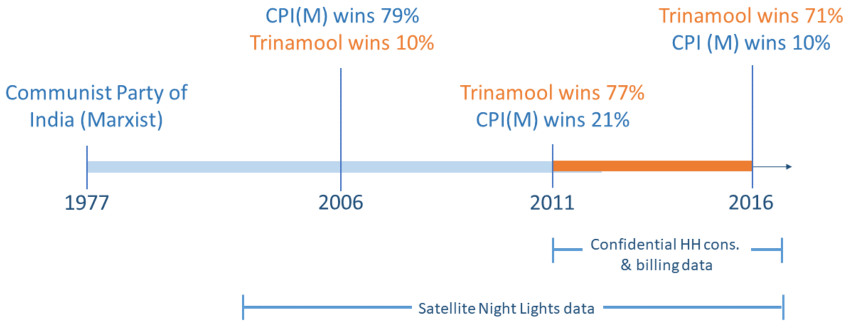
- Running variable: winning margin percentage, robust to total votes

Timeline Leading up to 2011 Election



RD Baseline Tests for 2011 Election

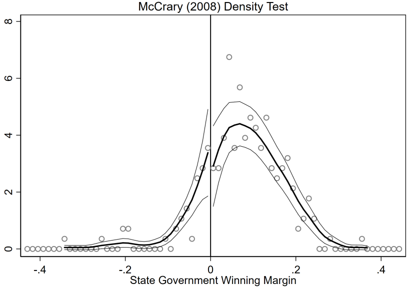


Figure: McCrary Test – density of winning margins at cutoff

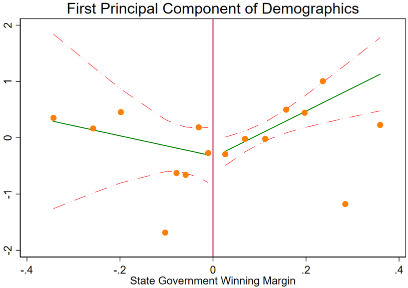


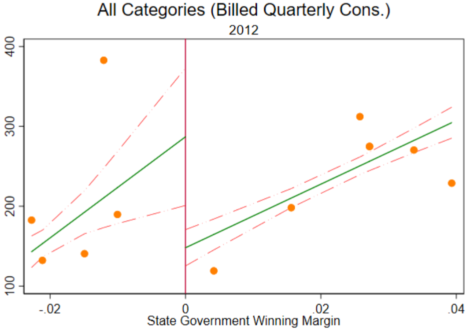
Figure: Balance on PCA of age, gender and caste

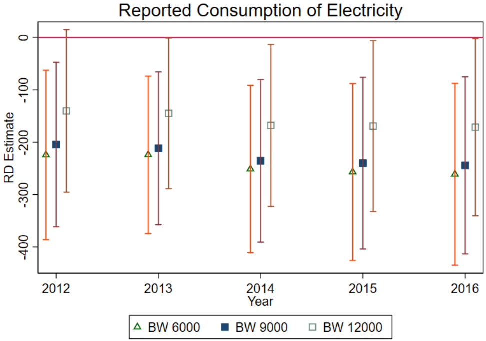
More Balance Tests

Lower Reported Consumption in Aligned Areas

- Optimal binning: >20,000 observations
- Reported consumption 40% lower in ruling party constituencies

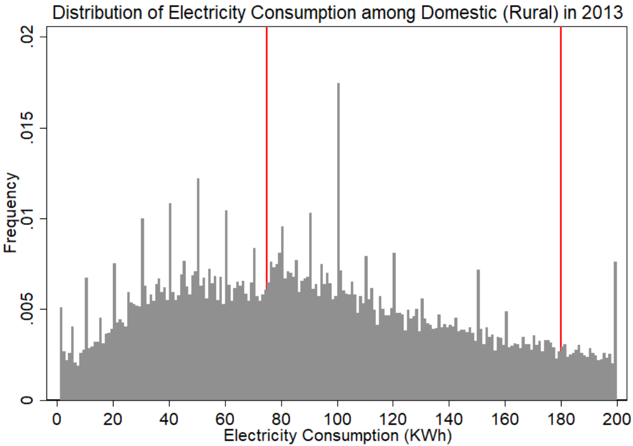
RD results by consumer category | Other billing items | Model





Spiky Consumption Distribution- Multiple Modes

- Red lines indicate kink points in the price schedule



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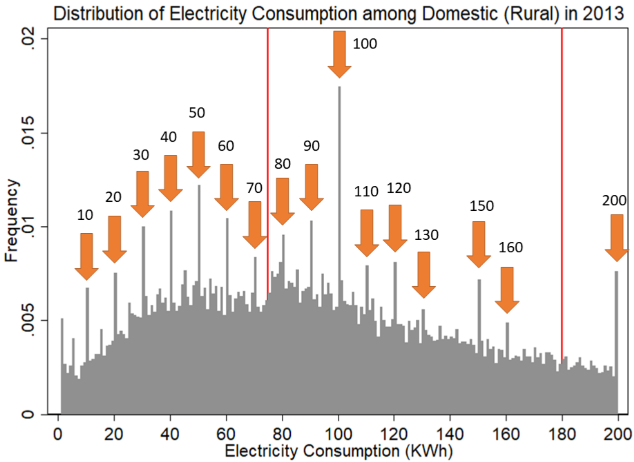
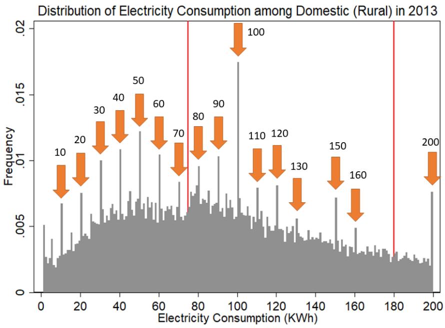
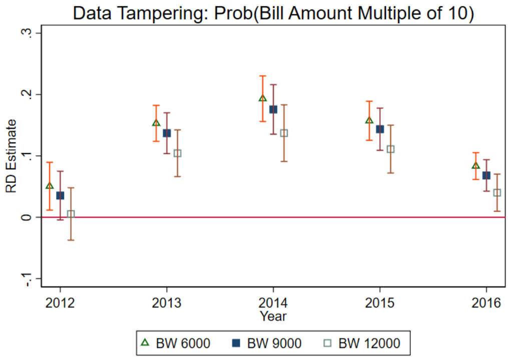


Greater Data Manipulation in Winning Areas

- Probability of bills ending in '0' **higher in winning constituencies**





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- Benford's Law (1938): Dist. for 1st digit of naturally occurring nos.
- Manipulation: deviation of observed from expected distribution

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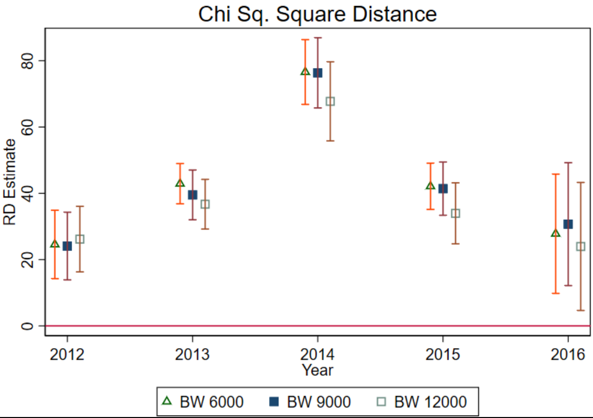
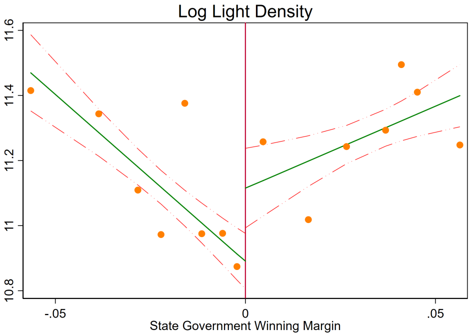
- Manipulation: deviation of observed from expected distribution
- **Higher manipulation in winning constituencies**

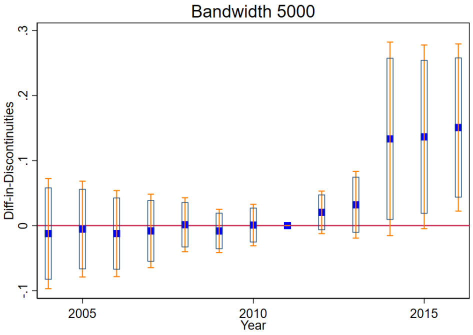


Higher Actual Consumption in Aligned Areas

- Contradicts result from billing data
- Optimal binning: 5-6 assemblies per bin

Regression Discontinuity specifications | Mapping light density | Falsification Test





Mechanisms of Patronage

1. Under-reporting of bills via local consumer care offices ✓
    - Billing centers vulnerable to politicians (Gulati & Rao 2007)
    - Meter inspectors do not go on rounds every billing cycle (Rains & Abraham '18)

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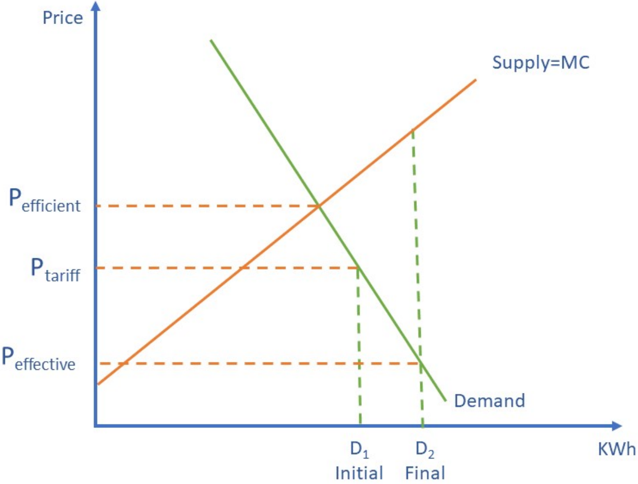
2. Selective energy theft in winning assemblies ✓
   - Utilities obstructed by MLAs (Times of India '17, Washington Post '12)

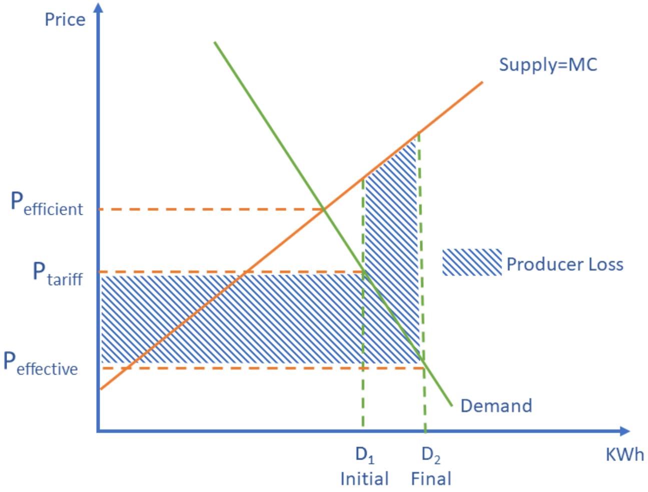
Welfare Analysis - Indirect Electricity Subsidy

- Under-reporting billed consumption: average price subsidy



Welfare Analysis - Indirect Electricity Subsidy

- Producer Loss: RD estimates of under-reporting X consumer base



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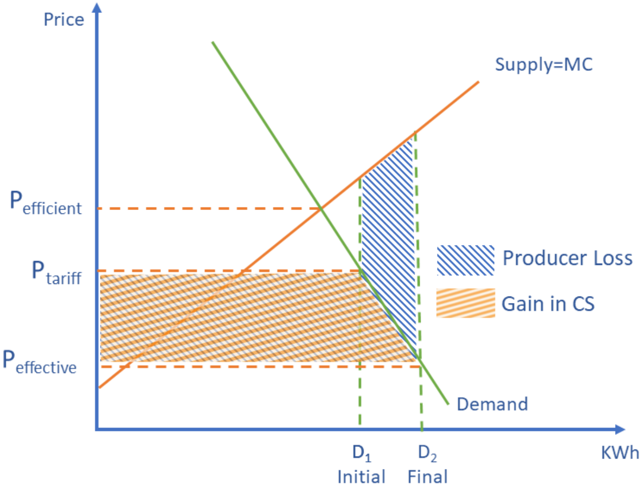
- Consumer surplus calculation: Need price elasticities of demand



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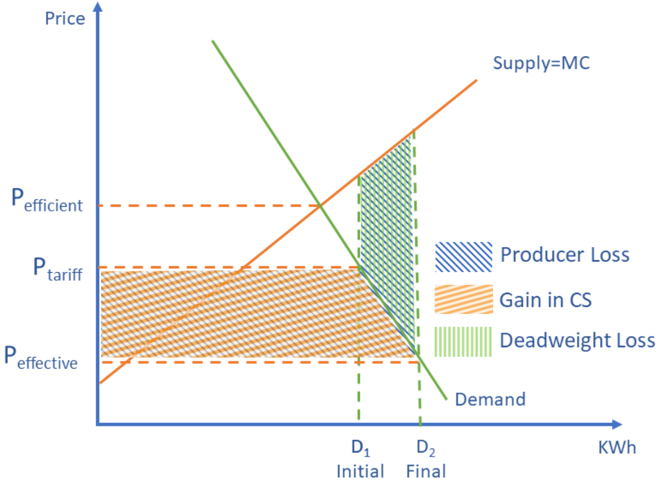

Demand Estimation - Under Data Manipulation

- Step 1: Select assemblies with no data manipulation
- Step 2: Elasticities for selected assemblies: IV strategy
- Step 3: Build prediction model: census village characteristics
- Step 4: Predict elasticities for out-of-sample assemblies
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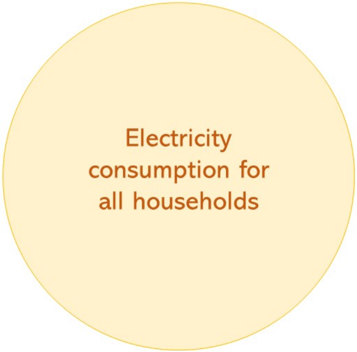

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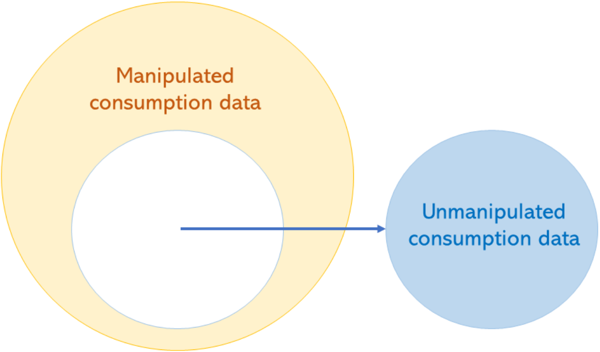

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STEP 2: Demand Estimation - IV Methodology

Identification Strategy

- OLS: price endogenous to consumption

$$\log\left(Consumption\right) = \delta \log\left(MarginalPrice\right) + \epsilon \tag{1}$$

- Similar identification strategy to Ito (2015): Instrumental Variable

IV specification

- IV- Policy-led changes in electricity tariffs: $\Delta \log\left(MarginalPrice\right)$

- Variation: tariff changes - 5 years X 5 price tiers X 4 categories

Demand Estimation - Under Data Manipulation

- Step 1: Select assemblies with no data manipulation
- Step 2: Demand elasticities for selected assemblies: IV strategy
- Step 3: Build model for prediction: census village characteristics
  - Two iterations of LASSO: penalizes irrelevant variables
  - Post-double-selection OLS (Ahrens et al. 2018) PDS Model
- Step 4: Predict elasticities for out-of-sample assemblies
- Step 5: Welfare estimates - producer & consumer surplus

STEP 3: Predictive Model for elasticities

- **Building predictive model**
- OLS: Biased or overfit
- Method: Post-double-selection OLS
  - Two steps of LASSO
  - OLS on selected model (unbiased β)
- Better for prediction

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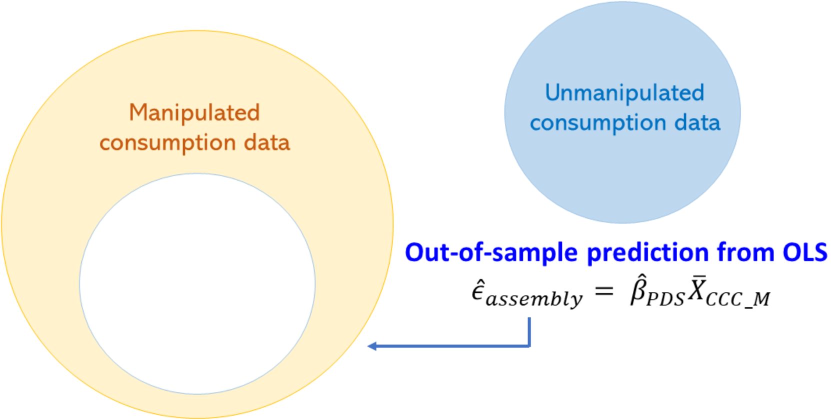
STEP 4: Demand Estimation - Projecting Elasticities



$$\hat{\epsilon}_{assembly} = \hat{\beta}_{PDS}\bar{X}_{CCC\_M}$$

Elasticity estimates

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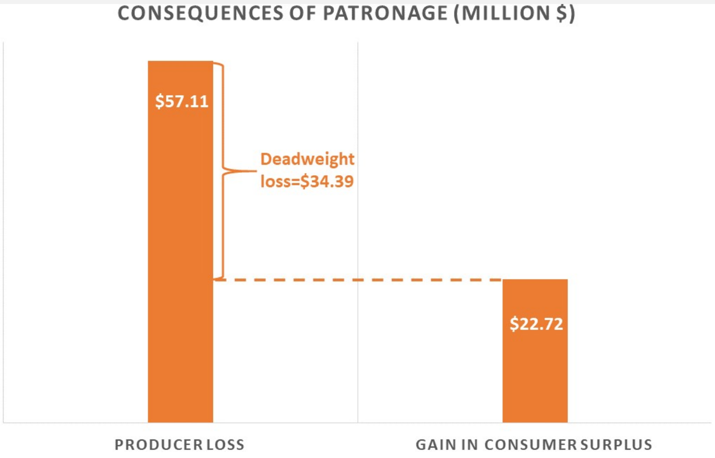
Lights-bills elasticity Targeting Patterns

STEP 5: Welfare Implications



- Totals for electoral term

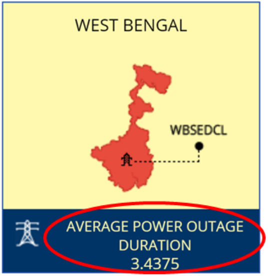
Welfare Calculations | Lights-bills elasticity | Targeting Patterns

Politicians in a position to benefit poor consumers

Credit:Wall Street Journal

Unintended consequences of targeting aligned constituencies

December 2018



SAKTIGARH	Scheduled	Sep 23, 2018 09:00 AM	Sep 23, 2018 02:00 PM	05:00 Hours
CHALKDIGHI 11 KV	Scheduled	Sep 22, 2018 09:00 AM	Sep 22, 2018 02:00 PM	05:00 Hours

1. **WBSEDCL - SANTIPUR KRISHNANAGAR**
THANA
Jan 14, 2019 9:00:00 AM
To Jan 14, 2019 4:00:00 PM

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  - Deadweight loss exceeds gains to consumers
- **Unintended consequences of patronage**
  - May harm the same constituents that politicians were favoring
  - Opportunity cost of using tax-payer funds

Comments welcome!

meeram@ucsb.edu

Model and Hypotheses

- Follow Dixit and Londregan (1996), Stromberg (2004)
- Consumers:
  - Consume electricity given prices and subsidies
  - Have preferences over political parties
  - Reward parties for cheaper electricity

$$U_{ia} = v(z_{ia}) + c \equiv \frac{exp^{\beta x_{ia}}}{1-\epsilon} z_{ia}^{1-\epsilon} + c \quad (2)$$

z_{ia}: amt of electricity, x_{ia} vector of consumer characteristics like amenities, infrastructure and regional income distributions,

$\epsilon > 0$: affects elasticity, p_{ia} "effective" electricity price, assembly a, political party i

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$$\textit{Demand Curve}: \; log\ z_{ia} = \frac{\beta}{\epsilon} x_{ia} - \frac{1}{\epsilon} log\ p_{ia} \tag{3}$$

Go back

Model and Hypotheses

- Political parties: Model of patronage
  - Want more votes
  - Exert effort (subject to resource constraint) to provide cheaper electricity

$$vote = \begin{cases} 1 & \text{if } exp^{\gamma D_{ia}} v(z_{ia}^{*}) > \eta_{ija} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

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$$e_{ia} = p_{ia}^{-\alpha} \tag{5}$$

  - Consumer utility rises with greater effort by party

$$v_{ia} = \frac{\left(exp^{\beta x_{ia}}\right)^{1+\frac{1}{\epsilon}}}{1-\epsilon} p_{ia}^{\frac{-(1-\epsilon)}{\epsilon}} = \frac{\left(exp^{\beta x_{ia}}\right)^{1+\frac{1}{\epsilon}}}{1-\epsilon} e_{ia}^{\frac{\alpha(1-\epsilon)}{\epsilon}} \tag{6}$$

Go back

Model Implications

Maximize prob. of winning, subj. to effort constraint

$$\max_{e_{i1},\ldots e_{1A}} \sum_a Pr\left(exp^{\gamma D_{ia}} v(z^*_{ia}) > \eta_{ija}\right) \quad s.t. \;\; \sum_a e_{ia} \leq E_i \tag{7}$$

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Political parties target:

Proposition 1: *Swing areas where in power*

Proposition 2: *Consumer categories with inelastic demand*

Proposition 3: *Consumers with access to better infrastructure*

Go back

Summary Statistics for Outcomes in Legislative Assemblies

	2012		2016	
	Winning	**Losing**	**Winning**	**Losing**
Number of Constituencies	184	42	184	42
Chi-Sq. Square Distance	26.59	11.85	34.42	32.33
Fraction of consumers with whole numbered KWH	0.15	0.16	0.13	0.13
Reported consumption (KWh)	260.55	174.39	270.96	181.27
Sum of all bill components (Rs.)	1533.27	979.10	1754.30	1117.91
Sum of all arrears (Rs.)	90.14	48.79	56.43	33.78
Average energy price per KWH (Rs.)	3.89	3.52	5.45	4.93
Average arrear per KWH (Rs.)	0.42	0.29	0.50	0.45
Total subsidies in Bill (Rs.)	-153.56	-104.56	-109.25	-79.19
Connected Load (KVA)	1.08	0.81	1.13	0.81

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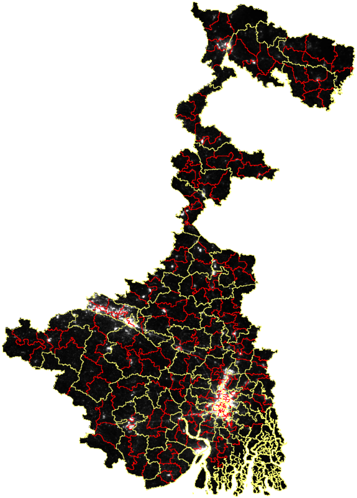
Mapping Nighttime Lights to Assemblies



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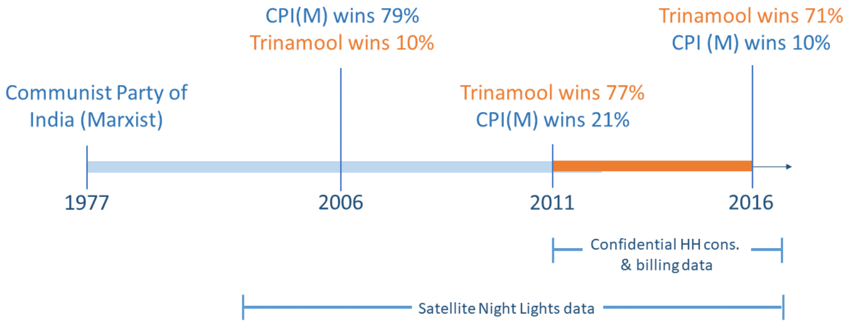
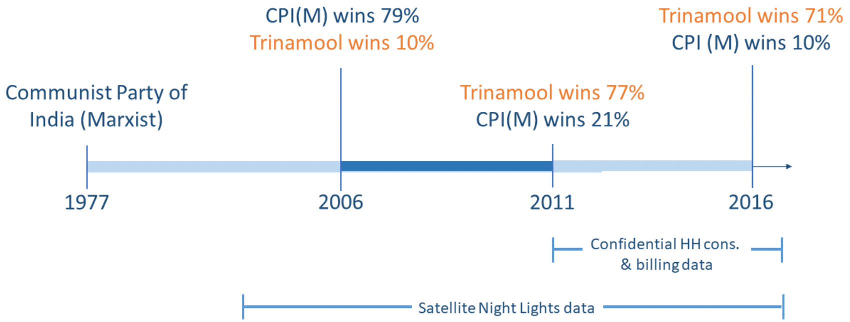
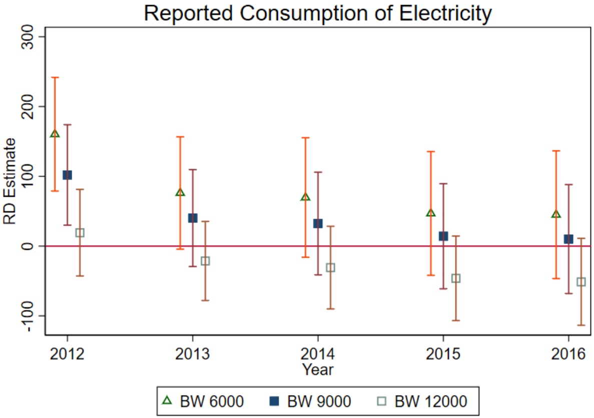


Swing constituencies from 2006 Election



Validity Check: Placebo Test Using 2006 Election

- Results using **assembly winning margins from 2006**
- No clear evidence of under-reporting with 2006 close-elections



	Log(Consumption Kwh/Quarter)			
	IV 2SLS **Unmanipulated Sample**	IV 2SLS **Manipulated Sample**	OLS **Unmanipulated Sample**	IV 2SLS **Aggregated to AC Level**
Log Marginal Price Residential Rural	-0.240 (0.293)	0.388* (0.228)	1.609*** (0.0596)	-0.137 (0.0972)
Log Marginal Price Residential Urban	-0.666** (0.310)	0.175 (0.220)	1.395*** (0.0574)	-0.019 (0.0916)
Log Marginal Price Commercial Rural	-3.158*** (0.585)	-1.364** (0.535)	0.583*** (0.130)	0.0628 (0.155)
Log Marginal Price Commercial Urban	-3.490*** (0.588)	-1.800*** (0.460)	0.595*** (0.111)	-0.206 (0.136)
Observations	83,787	120,087	106,937	13,943
R-squared	0.424	0.475	0.450	0.946
No. of Customers	21,581	30,906	21,980	
Fixed Effects	Month-Class Tier-Acc.	Month-Class Tier-Acc.	Month-Class Tier-Acc.	AC-Month Tier-Class
IV F-stat	579.8	704.2		414.6

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Independent Variables	Elasticity
Avg. no. of males under 6 yrs	-0.0122
	(0.170)
Avg. no. of females under 6 yrs	-0.000569
	(0.172)
Avg. no. of households	0.0106
	(0.0226)
Avg. no. of working males	-0.0126
	(0.0139)
Avg. no. of working females	0.0330**
	(0.0140)
Avg. no. of scheduled caste females	0.210**
	(0.0861)
Avg. no. of scheduled caste females	-0.197**
	(0.0814)
Avg. no. of scheduled tribe females	0.0153
	(0.0117)
Avg. no. of male cultivators	-0.0279**
	(0.0127)
Avg. no. of female cultivators	0.0339
	(0.0464)
Avg. no. of female workers (other)	0.00114
	(0.0416)
Avg. no. of literate females	-0.0156
	(0.0113)
Sq. of avg. no. of literate females	7.93e-06*
	(4.80e-06)
Constant	-50.99**
	(25.48)
Observations	43

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Unit consumption in KWH

			Residential (Rural)		
Year	**2012**	**2013**	**2014**	**2015**	**2016**
RD Estimate	-124.1***	-126.0***	-143.2***	-157.9***	-139.5***
	(24.33)	(20.58)	(21.08)	(22.57)	(23.70)
Observations	7,780	10,457	10,352	10,329	10,213
			Residential (Urban)		
RD Estimate	-311.4***	-366.2***	-382.9***	-401.8***	-433.1***
	(95.28)	(82.32)	(77.72)	(75.35)	(71.69)
Observations	9,630	11,417	11,350	11,260	11,075
			Commercial (Rural)		
RD Estimate	124.8	51.21	81.79	-16.16	107.4
	(99.62)	(78.51)	(70.12)	(80.87)	(88.63)
Observations	3,023	4,120	4,044	4,018	4,010
			Commercial (Urban)		
RD Estimate	-473.4*	-579.9**	-555.3**	-542.6**	-582.3**
	(273.20)	(250.70)	(234.50)	(265.40)	(291.80)
Observations	10,611	12,505	12,227	12,269	12,035

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STEP 4: Demand Elasticity Estimates for All Regions

Consumer Category	Elasticity of Electricity Demand
Residential (Rural)	-0.56
Residential (Urban)	-0.26
Commercial (Rural)	-2.94
Commercial (Urban)	-2.56

Counterfactual elasticities

- Residential elasticities similar to previous work
- Commercial elasticities higher than previous work: **-2.75 vs -0.65**

STEP 4: Demand Elasticity Estimates for All Regions

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Commercial (Urban)	-2.56

Counterfactual elasticities

- Residential elasticities similar to previous work
- Commercial elasticities higher than previous work: **-2.75 vs -0.65**
- More robust estimates than previous work
  1. Agg. data conceals manipulation
  2. Year level data misses consumption responses (and not well identified)
  3. Micro-data: observe tariff-tier variation

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Welfare Calculations

Consumer Class	Producer loss (Million Rs./year)	Gain in surplus (Million Rs./year)
Residential (Rural)	₹295.84	₹101.27
Residential (Urban)	₹323.77	₹177.80
Commercial (Urban)	₹111.41	₹11.76
Total (Million Rs./year)	₹731.01	₹290.83
Total (Million Rs./year)	₹3660.05	₹2401.95
Total (Million $ for 5 years)	**$ 57.11**	**$ 22.72**

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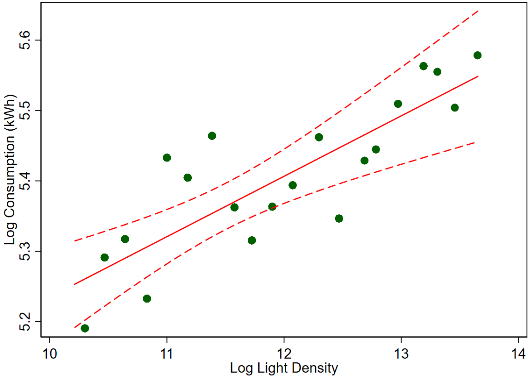
Nighttime Lights & Billed Consumption

- Increase in lights density: 20%
- Increase in electricity consumption: 1.7%



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RD Specification for Nighttime Light Density

- RD specification with differential linear fits on either side of the cutoff

$$Log(Lights)_a = \beta \, \mathbb{1}(votemargin > 0)_a + f(votemargin)_a + \epsilon_a$$

- Specification for difference-in-discontinuities

$$Log(Lights)_{at} = \sum_t \beta_t(\mathbb{1}(votemargin > 0)_a \times \gamma_t) + \gamma_t + f(votemargin)_a + \epsilon_{at}$$

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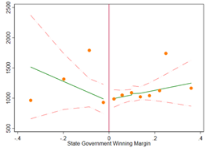
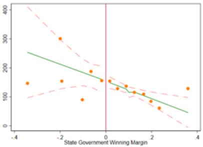
Balance Across RD Cutoff - Census Village-level Variables

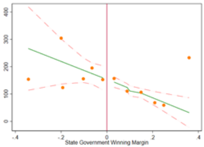


Avg. share of female population

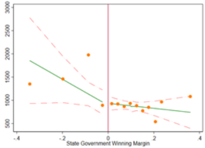
Avg. share of female workers



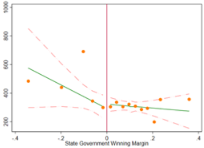
Avg. share of agri. workers



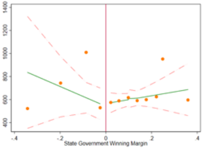
Avg. share of cultivators



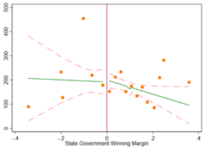
Avg. share of illiterate pop.



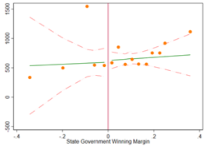
Avg. share of other workers



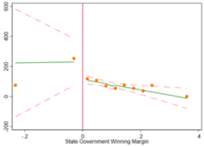
Avg. share of mfg. workers



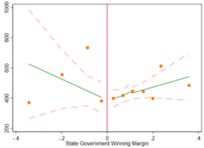
Avg. share of marginal workers



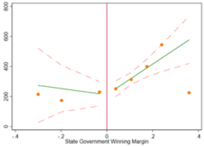
Avg. share of scheduled castes



Avg. share of scheduled tribes



Avg. share of non-mfg. workers



Avg. total population

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Consumers Categories Targeted by Politicians

	Unit consumption in KWH				
Year	**2012**	**2013**	**2014**	**2015**	**2016**
	All Residential Consumers				
RD_Estimate	-218.1**	-222.6**	-247.3***	-262.4***	-263.5***
	(97.22)	(91.64)	(91.07)	(87.53)	(97.13)
Observations	17,410	21,874	21,702	21,589	21,288
	All Commercial Consumers				
RD_Estimate	-109.3	-171.6	-151.8	-206.1	-130.0
	(154.5)	(144.9)	(137.1)	(139.3)	(159.8)
Observations	13,634	16,625	16,271	16,287	16,045
	All Rural Consumers				
RD_Estimate	-66.64*	-85.49***	-87.04***	-123.9***	-76.80**
	(35.80)	(33.00)	(28.16)	(34.10)	(34.00)
Observations	10,803	14,577	14,396	14,347	14,223
	All Urban Consumers				
RD_Estimate	-355.0***	-432.2***	-434.4***	-446.3***	-474.7***
	(116.8)	(106.9)	(97.21)	(106.7)	(107.9)
Observations	20,241	23,922	23,577	23,529	23,110

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STEP 2: Demand Estimation - Identification Strategy

First Stage

$$\log\left(MarginalPrice\right)_{iamtcy} = \sum_{a} \gamma_{ac} \Delta \log\left(PolicyTariff\right)_{iamtcy} + \nu_{mtc} + \zeta_{mac} + \eta_i + \varepsilon_{iamtcy} \quad \forall \ c \in C \qquad (8)$$

Second Stage

$$\log\left(Consumption\right)_{iamtcy} = \sum_{a} \beta_{ac} \log\left(\widehat{MarginalPrice}\right)_{iamtcy} + \tau_{mtc} + \mu_{mac} + \omega_i + \epsilon_{iamtcy} \quad \forall \ c \in C \qquad (9)$$

i consumer, c assembly, m month, y year, a consumer category, t price tier

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Patterns in Billing Items Consistent with Under-reporting

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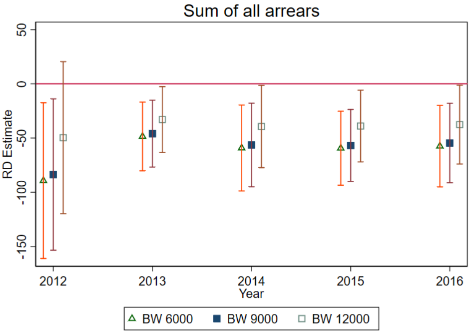

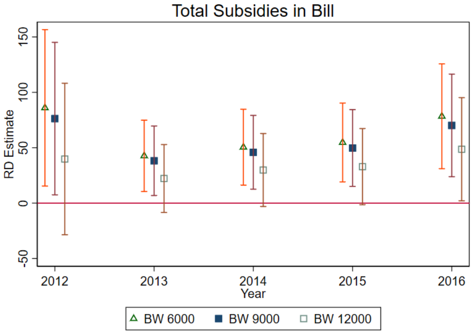

Patterns in Billing Items Consistent with Manipulation

- Connected load is the estimated amount of electricity demand that an account is registered for.

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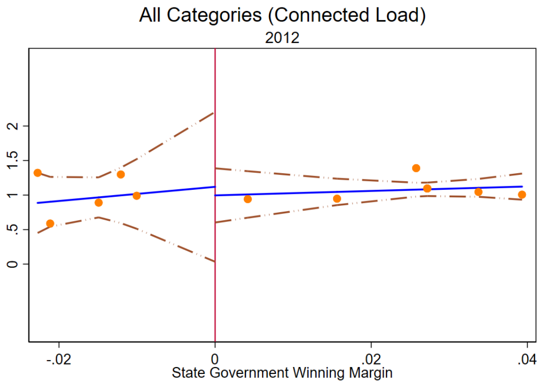

Political Targeting Patterns

Result 1: Party subsidizes swing areas where in power

- Manipulation in Reported Consumption
- Selectively allowing electricity theft

Result 2: Target more residential consumers

- Targeting low elasticity users (ϵ -0.41 vs -2.75)

RD table for targeting Model

Result 3: Target consumers in urban areas

- "Posh areas guilty of major power theft", *The Times of India*

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