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The Price of Power: Costs of Political Corruption in Indian Electricity[†]

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Politicians may target public goods to benefit their constituents, at the expense of others. I study corruption in the context of Indian electricity and estimate the welfare consequences. Using new administrative billing data and close-election regression discontinuities, I show that billed electricity consumption is lower for constituencies of the winning party by almost 40 percent, while actual consumption, measured by nighttime lights, is higher. I document the covert way in which politicians subsidize constituents by manipulating bills. These actions have substantial welfare implications, with an efficiency loss of US$0.9 billion, leading to unreliable electricity supply and significant negative consequences for development. (*JEL* D72, D73, L94, L98, O13, O17)

A classic concern in political economy is the extent to which legislators or bureaucrats favor the interests of some groups over others for political gain (Finan and Schechter 2012). A ruling party may provide their constituents with preferential access to public goods after winning an election to deliver campaign promises (Cruz et al. 2020) or instead target new voters in constituencies where they lost elections (Callen, Gulzar, and Rezaee 2020). Obtaining causal evidence of the mechanisms of patronage at a sufficiently large scale remains challenging (Muralidharan, Niehaus, and Sukhtankar 2016). However, identifying such practices and quantifying the welfare costs is the first order in designing effective policies and reducing inequities.

This work develops original forensic tools and uses new administrative data to examine the problem of political targeting through the lens of the Indian electricity

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sector. In many countries, public goods, such as electricity and water utilities, are state owned and therefore vulnerable to political manipulation. Public utilities offer a steady flow of resources that may be controlled by politicians even beyond their initial construction. There are numerous avenues to exploit the heavily bureaucratic and opaque processes behind investment and supply decisions to provide a continued stream of favorable access to preferred voter groups. While there exists some evidence on the costs of misallocation caused by patronage in general (Khwaja and Mian 2005), the impact on taxpayer-funded institutions themselves and the broader implications for welfare are harder to isolate in most contexts. For example, little is known about how much of the large commercial losses faced by public electricity providers and other state-run entities is attributable to political manipulation.[1] To the extent that such manipulation further hampers utilities' ability to provide reliable electricity, this has implications that go far beyond the electricity sector: the social costs of intermittent electricity on economic development (Dinkelman 2011; Greenstone and Jack 2015; Lipscomb, Mobarak, and Tania 2013) and productivity (Allcott, Collard-Wexler, and O'Connell 2016; Fried and Lagakos 2023) and the large opportunity costs of systematically bailing out loss-making electricity utilities (Chatterjee 2017). Despite the scale of these concerns, there is little evidence of well-identified work that describes political manipulation in large utilities (Min and Golden 2014) and even less on its ensuing welfare consequences.

This paper presents causal evidence on how Indian politicians may manipulate public electricity provision to favor a subset of voters and the large costs this imposes on electricity providers and the economy. I obtain new administrative billing records from the electricity utility of West Bengal, a large Indian state, to measure *reported* consumption. An innovation is to treat these administrative data as distinct from *actual* consumption, which this analysis measures using satellite nighttime luminosity data.[2] I argue that the difference between administrative data and actual usage serves as a proxy for potential manipulation, and this allows me to estimate its welfare implications in a way that is difficult to do in most other instances of corruption.

The paper presents three key results. In the first set of results, the paper provides causal evidence that politicians from the ruling party at the state level favor their constituents by providing them with illicit electricity subsidies after winning an election. I leverage a close-election regression discontinuity design (RDD), a strategy commonly used in political economy research in India and elsewhere (George and Ponattu 2020; Prakash, Rockmore, and Uppal 2019; Nellis, Weaver, and Rosenzweig 2016). We infer the existence of illicit subsidies based on two complementary pieces of evidence. First, shortly after a state-level election, there is an increase in *actual* electricity consumption, measured by satellite nighttime light data, for regions just aligned with the ruling party.[3] Second, these same regions in

[1] US$16 billion of taxpayer funds were used to bail out loss-making Indian electricity utilities. Losses amount to more than US$46 billion annually across Indian states (Denyer 2012).

[2] Satellite nighttime luminosity data have been found to be a good predictor of daytime electricity use, particularly in India (Mann, Melass, and Arun 2016).

[3] Throughout the paper, these results examine the role of a newly installed ruling party at the state level in the years before and following the election where they win. The results first focus on West Bengal, particularly after the 2011 elections, but show that these results extend to the rest of the country for elections from 2009 to 2022.

West Bengal have discontinuously lower levels of *billed* consumption, as reported by the electricity provider. The magnitude of underreporting is large, with favored account holders paying for only 60 percent of their billable consumption. Politicians appear to favor their constituencies by underreporting electricity consumption, even as their constituents consume higher actual amounts of electricity.

The second set of results uncovers the mechanisms by which bill manipulation takes place, a key feature in understanding how politicians may conceal data manipulation. First, we observe that a discontinuously higher number of bills in the ruling party's constituencies are multiples of ten, reporting consumption amounts such as 20, 30, 40 kWh, and so on—saliently visible in the underlying data. Given that each electoral district consists of three to four billing centers answering to the elected representative from the ruling party, these patterns point toward a top-down approach to manipulating reported consumption in the billing data. Second, to further corroborate these data anomalies, the paper uses Benford's (1938) Law to show that there is a greater divergence between the observed consumption distribution and the theoretically expected one in constituencies represented by the ruling party.[4] These results are consistent with incumbent local politicians rewarding their constituents by permitting the manipulation of billed consumption to appear lower than actual consumption, a mechanism made possible by the close relationships elected officials have with local billing centers (Chhibber, Shastri, and Sisson 2004). These findings explain the observed discrepancies between reported and actual electricity consumption, allowing me to identify the affected parties and assess the impact.

Finally, the paper discusses the welfare implications of billing manipulation by politicians. The combination of administrative data and satellite data in a context where corruption is measurable is instrumental in estimating the welfare consequences. We directly observe underreporting in billing data, and overconsumption of electricity through satellite nighttime lights data from the RD analysis, and use these estimates to compute the size of the welfare numbers. Welfare depends on the loss in producer profits from not recovering sufficient revenue and gains in surplus to a subset of benefiting consumers. The difference between the two provides a sense of the efficiency loss, if any. The paper estimates a loss to the electricity utility of over US$3.5 billion, while the favored set of consumers gain a sizable US$2.7 billion, creating a net efficiency loss of US$0.9 billion in West Bengal alone. In addition, these figures reflect losses for a single state, when in fact, electricity utilities in 25 other Indian states share similar vulnerabilities (Gulati and Rao 2007). Indeed, the paper finds the same patterns of overconsumption by connected constituents using nighttime lights data in other states and other elections in India.

At the broadest level, the paper contributes to a vast literature that aims to identify political patronage and corruption and demonstrates evidence at a large scale: first, for a state with a population of 72 million and then documenting similar patterns for the rest of the country. Other work has demonstrated the extent to which politicians have incentives to favor constituents, motivated by expected rewards in

[4] Benford's (1938) Law predicts a frequency distribution of the first digit of naturally occurring, unmanipulated sets of numerical data, such as consumption data, and is commonly used to detect data fraud in survey data collection.

subsequent election cycles (Fujiwara, Kanz, and Mukherjee 2020; Zimmermann 2021; George, Gupta, and Neggers 2018). However, the consequences for welfare are ambiguous, as reelection incentives could lead to an efficient allocation of government inputs (Pande 2020, 2003) rather than, as my results suggest, to efficiency losses. Given this ambiguity, documenting welfare costs in practice is important for designing policies to limit manipulation. My paper joins a handful of studies documenting the existence of welfare costs resulting from patronage practices (Khwaja and Mian 2005) and is one of the only ones to my knowledge that considers how large public institutions can be affected.

Measuring the scale of welfare costs from corruption is challenging and given the limited evidence on it (Hicken 2011), an important contribution of this paper. The few studies that examine the implications of patronage have often focused on preferential misallocation (Khwaja and Mian 2005). This paper advances the literature by considering an efficiency loss that goes beyond transfers. The unique combination of administrative and satellite data to distinguish between measured and true consumption is crucial in estimating welfare. Alone, the satellite data may indicate selectively higher levels of electricity access or consumption for politically connected regions. On the other hand, the billing data alone suggest, instead, that politicians redirect electricity to regions where they lost elections. However, taken together, the evidence from both datasets paints a different picture: that politicians may be underreporting electricity consumption for their constituents, and these consumers respond by overconsuming. These actions lead to a deadweight loss large enough to power almost 91 million additional rural households across the country. While beneficiaries may be gaining from illicit subsidies in the short run, they may bear the consequences of corruption in the long run through frequent outages due to the utility's limited ability to supply reliable electricity on insufficient revenue (Burgess et al. 2020; Mahadevan 2022). The true losses in efficiency are likely greater if one considers the opportunity cost of the electricity utility bailout (Chatterjee 2017) and the consequent inability of the utility to meet electricity needs, affecting economic productivity more broadly (Fried and Lagakos 2023).

The evidence on manipulation of administrative data for political purposes contributes to a large literature in public finance, where discussions about manipulation have often focused on inadvertent measurement error, incentives related to data collection, misreporting by consumers (Slemrod 2016), or eligibility manipulation (Camacho and Conover 2011). However, the role of political incentives to manipulate the measurement of consumption data itself is less studied. The political machine that enabled data manipulation in this context possibly extends to other types of administrative data (Jeong, Shenoy, and Zimmermann 2020), having implications for development policies that rely on those data. Although we may be able to observe the effects of patronage on economic growth or policy targeting from a well-identified setting (Asher and Novosad 2017), I show that more covert forms of patronage may be difficult to detect without comparing external or satellite data with on-the-ground administrative data. Having access to both micro-administrative and satellite data allows me to detect manipulation of the billing data and quantify the costs. In fact, regular audits of the electricity billing process failed to uncover this mode of corruption (Gulati and Rao 2007).

The layout of the rest of this paper is as follows. Section I presents a conceptual framework and institutional details. Section II describes the data used, and Section III covers the empirical strategy. Section IV presents evidence of corruption from administrative and satellite data. Section V discusses how the results extend to other contexts, and Section VI discusses the welfare implications. Section VII concludes.

I. Background and Conceptual Framework

Theoretically, the idea that politicians favor voters, particularly those in highly contested zones, is reflected in models developed by Stromberg (2004) and Dixit and Londregan (1996). On the one hand, they may redirect additional resources to closely contested regions where they lost elections (Callen, Gulzar, and Rezaee 2020). On the other hand, they may prefer to reward aligned voters to continue a cycle of electoral victories (Cruz et al. 2020; Mahadevan and Shenoy forthcoming). Targeting aligned regions may also be a result of lower costs (i.e., it is easier to influence local officials if the local MLA is a fellow party member).

Recent research shows that local representatives (the MLA or village council leaders) are the primary targets of credit or blame given the frontline role they play in the political machine (Shenoy and Zimmermann 2022; Mahadevan and Shenoy forthcoming), and this may occur independent of their party affiliation (Zimmermann 2021; Khanna and Mukherjee forthcoming). In fact, in south Asia, there is evidence that local leaders take credit for programs that were not even implemented by them, due to the immediate electoral payoff of these claims (Guiteras and Mobarak 2014). When centrally administered cash transfers occur, voters may actually be more likely to reward the local parties (when aligned to the ruling coalition) rather than rewarding the central government parties (Pop-Eleches and Pop-Eleches 2012). However, affiliation with the ruling party may crucially enhance the ability of local politicians to practice selective targeting (Asher and Novosad 2017), while hurting the ability of elected representatives from other parties to perform the same actions.

Controlling the electricity supply and billing could be advantageous for politicians, as any perceived improvements in service could result in better election outcomes. Continually poor electricity supply ensures that it is often a key electoral platform for politicians, as revealed by election surveys in India and other research (Chhibber, Shastri, and Sisson 2004; Chatterjee 2018). For instance, 55 percent of the firms surveyed in World Bank (2014) report experiencing electrical outages, and more than half the firms reported being required to provide a "gift" in exchange for an electricity connection. A third of the Indian population does not have access to electricity, and even those who do often experience long and frequent blackouts (Pargal and Banerjee 2014). Finally, poor electricity supply remains a major constraint to manufacturing (Allcott, Collard-Wexler, and O'Connell 2016).

However, at least on the surface, political control over the electricity sector may not always be easy or possible. Electricity providers in India remain state owned and managed by independent regulators, ostensibly separating politicians from decisions like setting electricity tariffs and overseeing the functioning of the utility. This institutional setup is ubiquitous across states in India, and similar to other countries (e.g., Brazil, Bangladesh, Mexico, Sri Lanka, and Kenya), where electricity is a heavily subsidized commodity for households and small commercial establishments. Further, using a large public sector like electricity provision as a tool of patronage may not be as straightforward as misallocating public funding or new infrastructure over which the politicians may have more direct control. To engage in patronage in the electricity sector, politicians would have to go through local civil servants who may not engage in corruption or may require bribes and threats. Second, they do not have the power to directly manipulate electricity pricing or supply, given the management of utilities by unaffiliated civil servants.

Nevertheless, politicians may find ways to exploit the financially ailing electricity sector, taking advantage of the institutional setup around it. For instance, in several states, electricity distributors have faced mounting losses for several years, but an individual state is rarely singled out (Chatterjee 2017, 2018). In fact, their bailout is virtually systematized under the central government program, Ujwal DISCOM Assurance Yojana (UDAY). Loss-making utilities that draw minimal attention, therefore, offer a potential avenue for politicians to exploit, despite the seeming lack of access. Indeed, Baskaran, Min, and Uppal (2015) show evidence of electoral cycles in power blackouts in India. Chatterjee (2018) presents evidence consistent with politicians pressuring regulatory officials to avoid upward revisions in tariffs, which regulators report resisting. There are anecdotes suggesting that politicians implicitly allow energy theft among their constituents (*Telegraph* 2014; Denyer 2012; *Times of India* 2018).[5] Golden and Min (2011) demonstrate how electricity bills are more likely to go unpaid in areas where criminals have political affiliations.

While politicians can take cover under an already loss-making sector, there do exist limits to the level of losses a utility can make before drawing unwanted attention. Excessive losses may attract central audits or unwanted media attention. Therefore, there may be an implicit constraint imposed to the extent of patronage by the “equilibrium” level of acceptable financial losses set by historical precedent and compared to other states. As a result, ruling parties may have an incentive to exploit the electricity sector to reward their constituents or allow their affiliated local representatives to do so. At the same time, they may have incentives to limit how much members of opposition parties can similarly exploit the sector because of (i) the implicit budget constraint imposed by past losses and (ii) constituents assigning credit to local representatives.

This paper first presents evidence on West Bengal, a large Indian state where the transmission and distribution sectors are state owned. The vast majority of consumers in the state (and most residential and commercial establishments) are supplied by the state-owned West Bengal State Electricity Distribution Company Limited (WBSEDCL), covering a population of about 72 million individuals through 17 million accounts.[6]

[5] “A [local politician] …. has said that discom officials who penalise farmers for power theft or overloading should be tied to trees.” *Times of India.* 2018. “Rajasthan BJP MLA Backs Farmers Stealing Power.” March 6.

[6] With the exception of one privately owned firm, which distributes only to the capital.

II. Data Description and Variable Definitions

A. *Administrative Data on Electricity Consumption and Billing*

This paper uses administrative data on the universe of electricity consumption and billing records from the West Bengal State Electricity Distribution Corporation Limited (WBSEDCL). These data include consumption for residential and commercial users in both rural and urban areas between 2011 and 2016. For most consumers, billing is done quarterly, with the exception of a few monthly users with commercial accounts. For the analysis in this paper, I restrict the analysis to a balanced panel of consumer IDs to ensure that I do not count any new accounts that started after 2012, and avoid issues of entry/exit. From the balanced panel of customers, I sample 2 percent of customer IDs, stratifying by each consumer category.

In the consumption dataset, each account is linked to a consumer care center (CCC). These centers are the local administrative offices for WBSEDCL, in charge of billing. I geo-locate each of the 510 CCCs and situate them within their respective legislative assemblies, resulting in 2 to 3 CCCs per assembly area. Through their CCCs, therefore, all account holders under WBSEDCL are assigned to a particular legislative assembly.

B. *Measures of Data Manipulation*

The consumption distribution for residential and commercial consumers in Figure 1 is multimodal, with bunching at specific points. The peaks in the data appear at round numbers such as 20, 30, or 40 kWh. Electricity meters are read before every billing cycle by meter readers employed by the electricity utility. While it is common for meter inspectors not to conduct readings every billing cycle and make imputations for interim periods, the spikes observed are large.

Based on the multimodal consumption distribution, I define two measures to characterize the manipulation of the underlying data. The first is based on Benford's (1938) Law, which lays out an expected distribution for the first digit of a naturally occurring set of numbers. I measure the normalized distance of the distribution of the first digit of consumption for each assembly-year from the expected distribution. This metric, which is the same as the χ^2 goodness-of-fit statistic, represents the degree of manipulation in the underlying data. The second measure I use is the fraction of consumers in an assembly, in any given year, who have a reported consumption that is a multiple of ten. Because the consumption data would be, in expectation, smoothly distributed, a multiple of ten should not occur discontinuously more just above the RD cutoff. These measures enable me to test whether there is selective manipulation of administrative data in assemblies closely aligned with the ruling party. If bills are manipulated to reflect lower than actual consumption, that would amount to an indirect subsidy to constituents.

C. *Satellite Nighttime Luminosity Data*

I use satellite nighttime lights data as a nonmanipulable measure of electricity consumption, serving as a barometer for the reported consumption from administrative

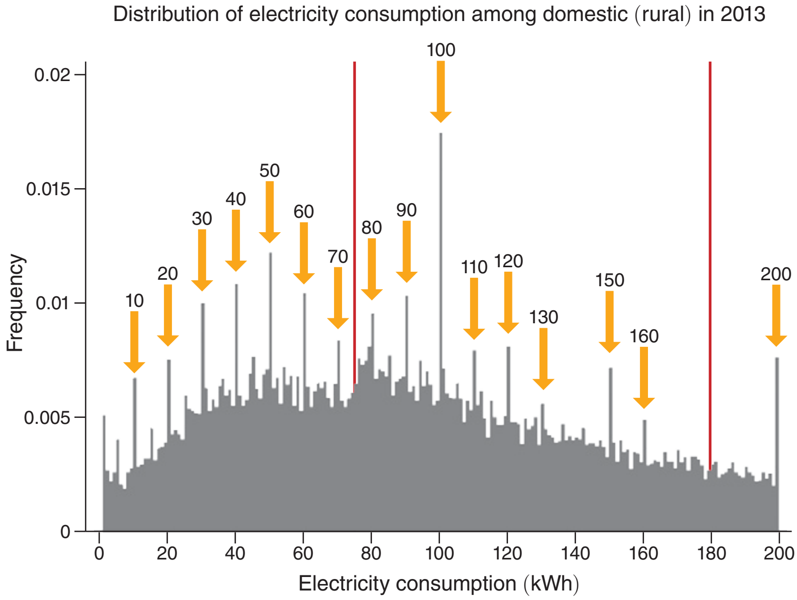

FIGURE 1. CONSUMPTION DISTRIBUTION FOR RESIDENTIAL CONSUMERS

Notes: The consumption distribution above is for residential consumers in rural areas. The range of consumption extends from 1 kWh to more than 1,000 kWh, but the bulk of distribution lies below 200 kWh (restricted to under this level in this graph) and largely has the shape of a χ^2 distribution. The two red lines represent the consumption levels at which the marginal price of electricity goes up a notch. There are several clear spikes in the distribution, and I find these particularly at multiples of ten.

data. I first validate this choice by checking if satellite nighttime lights are a good predictor of billed electricity consumption. Given the novel billing data, I can plot the relationship between selected billed consumption and luminosity data in online Appendix Figure A4.[7] This figure shows a strong linear relationship between log lights and billed consumption, validating the use of luminosity data as a measure of electricity consumption and also the use of the log functional form.[8] Luminosity data are also used to represent electricity consumption in other work; e.g., Mann, Melass, and Arun (2016) apply machine learning techniques to predict daytime electrification and show nighttime luminosity to be a good indicator of electricity consumption. This builds on previous work where luminosity data are used as a proxy for electrification: Baskaran, Min, and Uppal (2015); Burlig and Preonas (forthcoming); Min and Gaba (2014); Min et al. (2013); and Min and Golden (2014).

I use the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) satellite data from 2012 onward. I use a highly processed version that removes much of the noise, including cloud cover, ambient light, ephemeral lights, and background

[7] I use assemblies where the consumption data pass the Benford's Law test to ensure I am only using data with a low probability of having been manipulated in any way.

[8] I follow the literature in using log as my main functional form: this seems the standard practice in seminal papers across the literature, whether it is used at the national level (Henderson, Storeygard, and Weil 2012, 2011), at the subnational level (Alesina, Michalopoulos, and Papaioannou 2016; Storeygard 2016; Michalopoulos and Papaioannou 2013a, b; Hodler and Raschky 2014), or in papers that discuss whether and how to use VIIRS (Gibson et al. 2021).

(non-lights), and excludes any data impacted by stray light (Elvidge et al. 2013, 2017). VIIRS satellite data especially improve on low-light imaging compared to older satellite data such as the DMSP-OLS (discussed below), making across-region comparisons far more accurate. I measure the average density of lights within each legislative assembly, which is a continuous measure. In the absence of manipulation, the utility's consumption data may be expected to mirror patterns observed with the lights data.

I also use luminosity data from the United States Defense Meteorological Satellite Program (DMSP) for earlier years, which collects images of the earth twice a day and makes available annual composite images by averaging these daily data. They use 30–arc second grids, spanning −180 to 180 degrees longitude and −65 to 75 degrees latitude, and present the data using a 63-point luminosity scale. However, I use assembly-level average values of this luminosity, which yields a continuous measure of the variable.

I source both the VIIRS and DMSP-OLS measures by assembly from the publicly available Development Data Lab version 2.0 (Asher et al. 2021; Colorado School of Mines 2023; Henderson, Storeygard, and Weil 2011).

III. Close-Election Regression Discontinuity Design

This paper uses a close-election regression discontinuity (RD) design to identify whether politicians indirectly subsidize electricity. In India, parliamentary-style state elections occur every five years. States are composed of legislative assembly constituencies (in short, assemblies). The voting population elects assembly-level representatives or members of the legislative assembly (MLAs), and the political party with the majority of MLAs forms the government or the ruling party. This paper uses data on Indian elections from Asher et al. (2021) and Jensenius and Verniers (2017) from 2006 to 2022.

I compare outcomes just above and below a normalized winning vote margin RD cutoff to estimate the local average treatment effect (LATE) of being in an assembly aligned with a ruling party, after an election. The winning margin percentage is the fraction of votes by which an MLA from the ruling party wins an assembly election and is used as a running variable in other studies (Asher and Novosad 2017; Bardhan and Mookherjee 2010; Nagavarapu and Sekhri 2014). Assembly-level elections in India are competitive and unpredictable, and several factors affect their outcomes. Since the probability an assembly near the RD cutoff aligns with the ruling party is close-to-randomly determined, close election RDs may be especially valid here (Eggers et al. 2015).

In the 2011 state elections, the All India Trinamool Congress (AITC) defeated the incumbent Communist Party of India–Marxist (CPI(M)) (Figure 2) and won an absolute majority. I use state assembly election data from 2006 to 2017, covering West Bengal elections in 2006, 2011, and 2016, and discuss my data in greater detail in the next section. In online Appendix Section A, I further discuss details of the West Bengal elections. I focus on the 2011 election for results using administrative data. I use all election years between 2006 and 2022 to examine patterns in the nighttime lights data across other states in India and highlight the external validity of the main results. Online Appendix Table A1 presents summary statistics for the

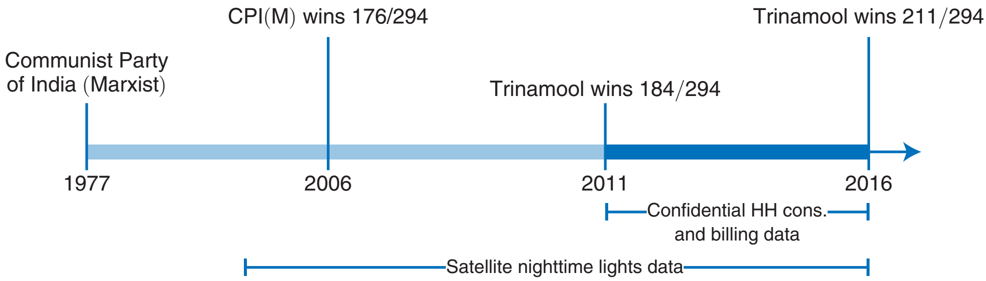

Figure 2. Timeline of State Elections in West Bengal from 1977 to 2016

Notes: This figure shows multiple election years for the West Bengal State Legislative Assemblies. Between 1977 and 2006, the Communist Party of India (Marxist) won an absolute majority in the legislative elections. In 2011 and 2016, the All India Trinamool Congress won the absolute majority of seats, which means that they did not need to form any alliances with other political parties to form the state government. The administrative billing data coincide perfectly with the 2011 electoral term with the AITC as the ruling party.

main variables of interest by whether or not the assembly was aligned with the ruling party. The table presents the summary measures for each of the samples used in the data, varied by the bandwidth applied in each RD. In the analysis using billing data, I focus on the 2011 election. All analyses using billing and consumption data analyze political behavior post elections.

An important issue when using the RD is the selection of a smoothing parameter (Imbens and Lemieux 2008; Imbens and Kalyanaraman 2012; Calonico, Cattaneo, and Titiunik 2015). In particular, I estimate local linear regressions with a rectangular kernel and employ the optimal data-driven procedure and bandwidth selection in Calonico, Cattaneo, and Titiunik (2015). I present my results for a wide range of bandwidths to highlight the robust nature of my estimates, varying them from well below the optimal bandwidths to larger bandwidths. Varying the size of the bandwidth and the polynomial order does not affect the results presented in my analysis.

Two checks for balance of the running variable, the winning vote margin, and other demographic characteristics of the assemblies on either side of the cutoff validate the use of the RD. The McCrary (2008) test finds no significant discontinuities in the density of the running variable across the cutoff (Figure 3). Figure 4 further checks for balance across a range of village-level characteristics from the 2011 Indian census (ML Infomap 2011) and finds no significant discontinuities in demographic characteristics such as the proportion of certain castes, females, literate people, agricultural workers, and children. Online Appendix Figure A1 shows the McCrary test limited to the bandwidth and finds no discontinuities.

IV. Empirical Evidence of Political Patronage

I leverage the close-election RD to test whether the party in power illicitly provided differentially cheaper electricity access to its voters by comparing electricity provision across the RD cutoff, using both administrative (reported consumption) and satellite data (actual consumption) (ML Infomap 2011; Susewind 2014; and Mahadevan 2024). I also explore the mechanisms behind potential corruption by examining patterns in the within-region distributions of electricity consumption. Throughout the paper, I refer to the party that wins an election as "ruling party" at

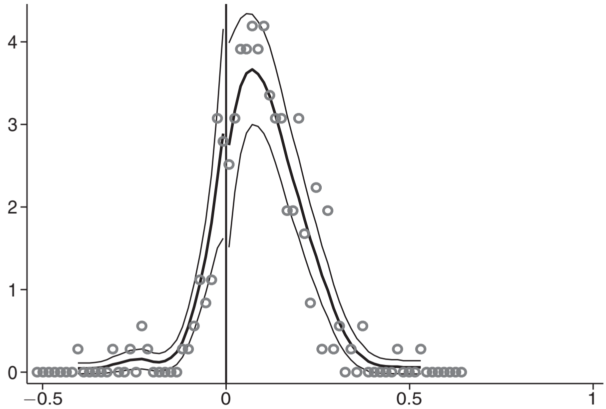

FIGURE 3. BALANCE ACROSS RD CUTOFF MCCRARY TEST

Notes: I test the smoothness of the running variable density (winning margin in the 2011 state election) and find no discontinuities across the RD cutoff using the McCrary test. The running variable takes on the value of the vote share percentage with which a candidate from the ruling party won their legislative seat, and it is at assembly level. I do not find any discontinuities in the running variable even after narrowing in on the optimal bandwidth, as shown in online Appendix Figure A1.

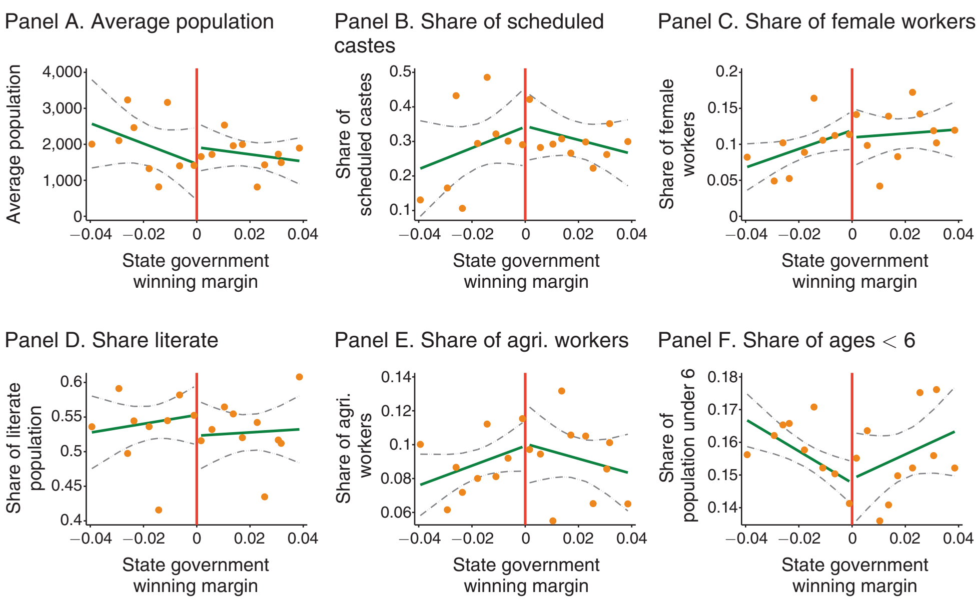

FIGURE 4. BALANCE ON DEMOGRAPHIC FEATURES ACROSS RD CUTOFF

Notes: I test for balance across the RD cutoff of a range of assembly characteristics sourced from the Indian Population Census 2011. I show the RD plots for a range of characteristics at assembly level, restricting the running variable to a bandwidth of 4 pp, which is the optimal bandwidth I use for all outcomes throughout the paper. I find no evidence of discontinuities across the cutoff. The regression discontinuity estimates for each outcome are also presented in online Appendix Table A4.

the state level in the years following the election. I refer to the assemblies where they win or lose as "winning" or "losing" assemblies, respectively. I also refer to assemblies "aligned" with the ruling party as assemblies where the ruling party wins the election.

I use a bandwidth of 4.169 percentage points as the winning margin percentage, corresponding to about 6,650–7,109 votes. This is the optimal bandwidth under the Calonico, Cattaneo, and Titiunik (2015) method using the billed consumption from the administrative data. I maintain this bandwidth across outcomes for consistency and ease of interpretation but show robustness to a range of bandwidths from 1.6 pp up to 7 pp (I show the effective sample sizes and summary statistics in online Appendix Table A1). To contextualize this in the literature examining close elections in India, these vote margins are lower or comparable to those used in Asher and Novosad (2017) (3–20 percentage points); Brown, Mansour, and O'Connell (2021) (5 percentage points); Prakash, Rockmore, and Uppal (2019) (6.16–7.79 percentage points); Bhalotra, Clots-Figueras, and Iyer (2018) (16–21 percentage points); Lehne, Shapiro, and Vanden Eynde (2018) (3–6.2 percentage points); and Clots-Figueras (2012) (6–9 percentage points), who all examine close elections in India.

A. *Average Nighttime Lights Density*

I estimate the following specification at assembly level a, where the vote margin is the net difference in the fraction of votes received by the winning party over the party with the second-highest votes:

$$\log(Lights)_a = \beta \mathbf{1}\{vote\_margin > 0\}_a + f(vote\_margin)_a + \varepsilon_a \quad \text{for } a \in BW. \tag{1}$$

Here, $f(vote\_margin)_a$ controls for the vote margin running variable, and BW is the optimal bandwidth around the cutoff. I test for discontinuities in the average light density around the RD cutoff, allowing for the slope of the vote margin to vary at the cutoff. β measures the RD coefficient. Given that the RD estimates the LATE, I make causal claims for the subsample of assemblies close to the winning margin cutoff. Table 1 shows that assemblies narrowly aligned with the ruling party consume 0.53 log points more electricity than those that do not, after the 2011 elections. Given balance across the RD cutoff on the running variable and underlying assembly demographics (Figure 3), this discontinuity suggests differential treatment by the politicians in power.

Figure 5, panel A demonstrates that there is discontinuously higher light density for assemblies where the ruling party narrowly won. To further investigate this pattern, I use nighttime lights data from 2006 to 2016. I study how being above the 2011 winning margin cutoff affects light density both before the elections (2007–2010) and after (2012–2016). The pre-2011 years serve to check whether there was a pre-election trend toward discontinuously higher electricity consumption. The coefficients after 2011 map out the post-election dynamics, as a consequence of the assembly being aligned with the ruling party. I estimate a

Table 1—Discontinuity in Actual Electricity Consumption (West Bengal)

Variables	log(*lights*) (1)	log(*lights*) (2)	log(*lights*) (3)	log(*lights*) (4)	log(*lights*) (5)	log(*lights*) (6)	log(*lights*) (7)
RD_Estimate	0.333	0.461	0.522	0.526	0.523	0.504	0.441
	(0.097)	(0.104)	(0.106)	(0.106)	(0.102)	(0.101)	(0.100)
Observations	155.0	190.0	220.0	240.0	285.0	325.0	345.0
BW (win margin pp)	2.5	3.0	3.5	4.0	4.5	5.0	5.5

Notes: This table tests for a discontinuity in log(lights) across assemblies that are aligned and not with the ruling party versus not, and presents the RD estimates from equation (1) for a range of 7 bandwidths ranging from 2.5 to 5.5 pp winning margin. The bandwidth of 4 pp closely approximates the optimal bandwidth, which has been used consistently across all billing and night-lights outcomes. This table shows evidence of discontinuously higher actual electricity consumption in West Bengal after the 2011 elections, from 2012 to 2016. Online Appendix Figure A10 shows robustness of these results for a wider range of bandwidths. Standard errors in parentheses clustered at the assembly level.

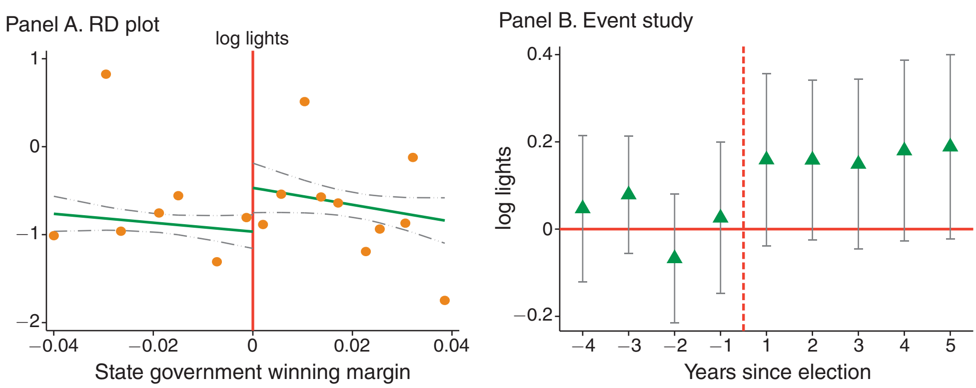

Figure 5. Satellite Night-Lights: RD Plot and Difference-in-Discontinuities Analysis

Notes: In panel A, I test for a discontinuity in log(nighttime lights) across assemblies that are aligned and not with the ruling party, using equation (1) at assembly level. I find that there is a discontinuously higher density of nighttime lights in assemblies just aligned with the ruling party after the 2011 election (2012–2016). Panel B plots an event study using log(lights) over time (2007–2016) and finds a trend break after the 2011 election in West Bengal, with selectively greater electricity consumption in areas where the ruling party narrowly won in 2011. This figure follows the specification in equation (2), and the regression is run at assembly-year level, with an optimal bandwidth of 4 pp. Online Appendix Figure A10, panel A shows robustness of these results for a wide range of bandwidths from 2.5–7 pp. Standard errors clustered at the assembly level.

difference-in-discontinuities specification, described by equation (2), which includes year γ_t and assembly fixed effects μ_a and restricts the sample to a bandwidth around the cutoff. β_t is the coefficient of interest across years.[9]

$$\log\left(Lights\right)_{at} = \sum_t \beta_t\left(\mathbf{1}\left\{vote\_margin > 0\right\}_a\right) + \gamma_t + \mu_a + \varepsilon_{at} \tag{2}$$

$$for\ a \in BW,\ t \in \left[-4, 5\right] \text{ and } t \neq 0.$$

[9] In 2016, West Bengal had 294 assemblies spread across 23 administrative districts.

On graphing these coefficients in Figure 5, panel B, I observe that there was no discontinuity or differential electricity consumption in the years before the 2011 elections. After 2011, there is a break, and I observe an increase in differential electricity consumption in assemblies where the ruling party narrowly won. Taken in isolation, this evidence may imply that there is differential access to electricity that is provided to the constituents of the winning party. However, this alone is not sufficient to understand the underlying dynamics, as I show using the administrative billing data below.

B. *Data Manipulation in Electricity Billing Records*

Administrative individual-level consumer data directly obtained from the state utility provide a useful companion to the satellite data described above. While the satellite data indicate actual electricity consumption, billing data document consumption as reported by the utility. Similarities or divergences between these two datasets could be useful in understanding potential corruption by politicians. I show evidence of a discontinuity in Figure 6 using consumption data on all consumer classes, including households, commercial users, public works, agriculture, and irrigation.[10] For each post-election year and consumption category, I estimate the following specification at the individual i account level, where the outcome is electricity consumption. I present the consumer-wise RD results in Table 2. The table shows a statistically and economically significant level of discontinuously lower reported consumption for residential consumers and commercial urban consumers.

$$(3) \quad y_{ia} = \beta \mathbf{1}\{vote\_margin > 0\}_a + f(votemargin)_a + \varepsilon_{ia} \quad for \quad a \in BW.$$

In Figure 6, using the consumption data reported by the electricity utility, I observe a discontinuously lower level of average electricity consumption in assemblies that narrowly swung in the ruling party's favor. I find this to hold using a wide range of bandwidths from 1.6 pp to 7 pp (see online Appendix Section D). Further, the magnitudes of these discrepancies are large, amounting to average discounts to constituents of about 40 percent of their regular bills.[11] This result is in contrast to the previous section, where we observed a discontinuously higher level of nightlights density.

A potential possibility with using satellite data is that it may primarily capture an increase in the extensive margin of electricity consumption, which billing records may not capture. Indeed, the Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) in India, launched in 2005, sanctioned the electrification of unelectrified villages all over the country. Looking at the assemblies just below and above the RD cutoff, the

[10] The only consumer class not present in the dataset shared with me is high-tension industrial consumers of electricity (usually large factories). However, this does not present a concern for the results in the paper because, given that factories do not commonly operate at night, the nighttime lights data should closely correspond to the consumers captured in the billing dataset.

[11] These magnitudes are based on a simple calculation using the estimated effects of being in an aligned assembly, and the average electricity consumption at the cutoff in opposition-party assemblies.

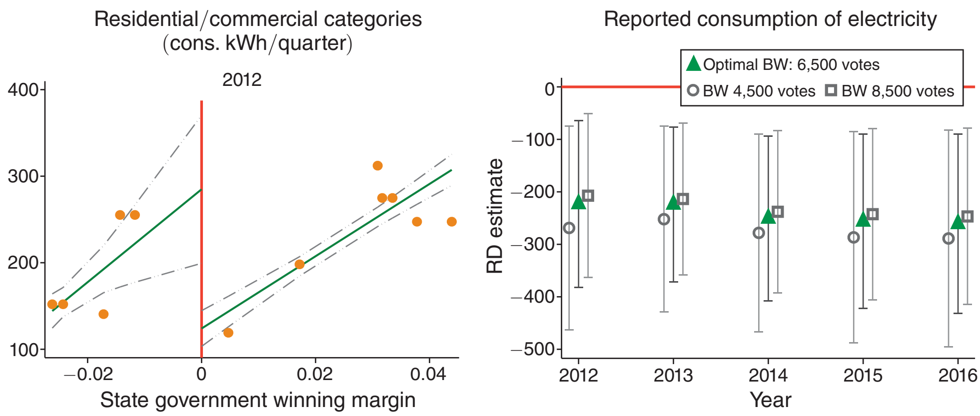

Figure 6. Lower Reported Consumption in Regions Where the Ruling Party Won, 2012–2015

Notes: The left-hand panel plots the reported consumption of electricity on either side of the RD cutoff, following equation (3) at individual consumer level. The running variable for the RD is the winning margin percentage for a ruling party candidate. The optimal bandwidth is ± 4.17 percentage point vote margin for the ruling party, which corresponds to a winning margin of $-7{,}109$ to 6,650 votes in various assemblies. In the right panel, I plot the RD coefficients between 2012 and 2016, running equation (3) separately for each of the years. I find results robust to other bandwidths (in terms of the number of votes) between $\pm 4{,}500$ and $\pm 8{,}500$ votes, showing 95 percent confidence intervals. Here, a $\pm 4{,}500$ vote margin corresponds to between -2.74 and 3.18 percentage point, 6,500 votes corresponds to between -3.88 and 4.45 percentage point, and 8,500 votes correspond to between -5.77 and 6.31 percentage point vote margin for the ruling party. These results remain robust to much smaller and much bigger bandwidths as well from 1.6 pp to 7 pp winning margin percentage (online Appendix Sections D.2 and D.4). Standard errors are clustered at the feeder level and are robust to clustering at the assembly level (online Appendix Figure A12).

Table 2—Discontinuity in Reported Consumption

	Cons (kWh) (1)	Cons (kWh) (2)	Cons (kWh) (3)	Cons (kWh) (4)
RD_Estimate	−139.850	−408.013	58.552	−635.530
	(19.268)	(87.667)	(69.775)	(281.019)
Observations	53,084	58,225	20,946	66,623
Consumer	Residential	Residential	Commercial	Commercial
Region	Rural	Urban	Rural	Urban
BW (pp)	4.170	4.170	4.170	4.170
p-value diff		0		0

Notes: I test for a discontinuity in reported consumption from billing data in assemblies just aligned with the ruling party versus not. I perform this RD analysis at individual consumer level for four different consumer categories: residential consumers (urban and rural) and commercial users (urban and rural), following the specification of equation (3). This table reports the RD coefficient for each class of consumers. The results in this table use a bandwidth of 4.17 vote share percentage in terms of the running variable, the winning margin of the ruling party candidate. The last line of the table presents the *p*-value of the difference between the rural and urban RD estimates for residential and commercial accounts. The *p*-values of 0 indicate that the RD estimates across rural and urban accounts are statistically different from each other at 99 percent significance. This table shows evidence of discontinuously lower reported consumption for assemblies just aligned with the ruling party at state level. These results are robust across a range of bandwidths (online Appendix Sections D.2 and D.4) and for each year in the electoral term 2012–2016 (online Appendix Table A3). Standard errors in parentheses clustered at the feeder level.

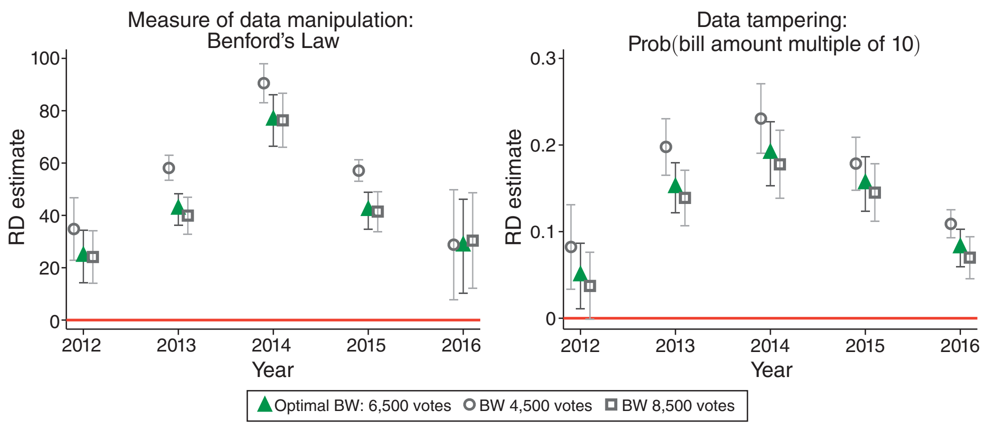

FIGURE 7. RD COEFFICIENTS FOR MANIPULATION OUTCOMES ACROSS BANDWIDTHS

Notes: I test for a discontinuity in measures of data manipulation from billing data in assemblies just aligned with the ruling party versus not. I perform this RD analysis at individual consumer-year level following the specification in equation (3) with two main outcome variables: the distance between the actual within-assembly consumption distribution and the theoretically expected distribution under Benford's Law, and the probability that the reported consumption is a multiple of ten (based on the observation in Figure 1). I plot coefficients across years for measures of data manipulation, and confidence intervals of standard errors clustered at the electrical-feeder level. Specifically, I study the distance of the observed distribution from the expected distribution as per Benford's (1938) Law and the fraction of consumers whose consumption was a multiple of ten. "BW" indicates the bandwidth size. The bandwidth of 6,500 votes corresponds to the optimal bandwidth of 4.17 pp winning margin percentage used throughout this paper. For both outcomes, I plot the RD coefficients between 2012 and 2016 and find results robust to other bandwidths—both lower and higher than the optimal bandwidth of 6,500 votes (between 4,500 and 8,500 votes). I control for the total size of the electorate within each assembly.

number of villages receiving electricity connections through the RGGVY scheme is very similar: 5,944 compared to 6,024 in assemblies aligned with the ruling party.[12] Further, the bulk of new electrification in India happened before 2011. Aside from the rural electricity connections scheme, it is, of course, possible that part of what the nighttime lights captures is selectively provided new connections to voters. This possibility of extensive margin patronage is important to consider and may exacerbate negative distributive consequences of patronage in electricity.

Next, I examine patterns in the data that may shed light on the observed underreporting of electricity consumption, using the measures of data manipulation described in Section IIB. In Figure 7, I find that the measure of distance (of the consumption distribution) from the expected χ^2 distribution (based on Benford's (1938) Law) is statistically significantly higher in assemblies just aligned with the ruling party. These results are echoed by the RD on the likelihood of billed consumption being reported as multiples of ten, which is systematically higher in assemblies represented by the ruling party. Ex ante, there would be no reason for these areas to see an anomalously high incidence of kWh that are neatly rounded off, but coupled with Figures 5 and 6, the results point toward politically motivated underreporting of electricity consumption in assemblies aligned with the ruling party. The degree of data manipulation grows over time, and then the discontinuity falls by 2016, on the eve of the next election. From

[12] Author calculations from statistics by the Ministry of Power, India (Central Electricity Authority 2013).

Table 3—Discontinuity in Data Manipulation

Variables	West Bengal 2011 Benford's (1)	West Bengal 2011 kWh-10 (2)
RD_Estimate	39.359	0.124
	(4.603)	(0.009)
Observations	75,015	75,015
BW pp	4.170	4.170

Notes: I test for a discontinuity in measures of data manipulation from billing data in assemblies just aligned with the ruling party versus not. I perform this RD analysis at the individual consumer level following the specification in equation (3) with two main outcome variables: (i) the distance between the actual within-assembly consumption distribution and the theoretically expected distribution under Benford's Law, (ii) and the probability that the reported consumption is a multiple of ten (based on the observation in Figure 1). The results in this table use a bandwidth of 4.17 vote share percentage in terms of the running variable, winning margin of the ruling party candidate. This table shows evidence of discontinuously higher levels of data manipulation in assemblies just aligned with the ruling party at state level. These results are robust across a range of bandwidths (online Appendix Figures A8 and A9). Standard errors in parentheses clustered at the feeder level.

the available data, it is difficult to distinguish if this occurs because there is a higher degree of data manipulation in losing assemblies as well or that politicians direct their efforts elsewhere in the run-up to the next election. Table 3 presents the regression discontinuity estimates for measures of data manipulation after the election in 2011, until 2016. The table shows that there is a statistically higher likelihood of data manipulation in assemblies aligned with the ruling party.

C. *Mechanisms of Political Corruption in Electricity*

This paper presents evidence that there may be a systematic underreporting of electricity consumption in the state of West Bengal by manipulating billed consumption for connected constituents. In the Indian context, the setup of the bureaucracy around electricity provision appears well suited to control by local representatives, given the close oversight of local electricity billing and distribution centers. There is research in other contexts to suggest that politicians can indirectly influence lower levels of the bureaucracy that may be involved in day-to-day transactions reflected in administrative micro-data (Lowe, Prakash, and Rajendran 2020; Weaver 2021; Barnwal 2019; Neggers 2018).

There are a number of ways that the electricity sector may be susceptible to manipulation. Electricity meter readings provide one of the few manipulable margins on which to affect electricity prices. In order to bill consumers, electricity utilities send meter readers to account holders' premises to manually record consumption. To a large extent, due to the absence of additional checks, reported consumption is up to the discretion of these meter inspectors and the local Customer Care Centers they report to, who then manually enter their reported consumption figures into the database. This is a possible point at which underreporting occurs.[13] Indeed, among

[13] Over the course of my fieldwork, I observed several instances of meter readers not conducting their inspection rounds for multiple billing periods. While the billing center handbooks recommend a formula to impute consumption

several vulnerabilities, Gulati and Rao (2007) identify the billing stage as susceptible to political interference, highlighting artificially lowered bills as a specific example. An audit study carried out by an electricity utility in Uttar Pradesh, another Indian state, identified significant political interference in electricity distribution and billing at local levels (Goenka 2013). Rains and Abraham (2018) highlight the role of these inspectors in bill collection and how redesigning their incentives could lead to massive gains in utility revenue. My findings are consistent with a selective lack of enforcement in inspector readings, in order to allow local billing centers under the purview of the MLAs to report billed consumption that is lower than actual levels. Further, it is a relatively low effort to systematically underreport electricity consumption as a part of the routine data entry, making this type of political targeting quick to implement after an election.

Another way politicians may exploit the electricity sector is by selectively discouraging utility action against energy theft. Even though I am unable to test this directly, there is a large amount of anecdotal evidence supporting this (Denyer 2012; *Times of India* 2017; *Telegraph* 2014).[14] While this is consistent with lower reported consumption and higher actual consumption, it cannot alone explain the discontinuously higher levels of data manipulation in assemblies controlled by the ruling party.

V. External Validity and Robustness Checks

The empirical results presented so far focus on West Bengal because of the availability of state administrative billing data from 2012 to 2016. However, satellite nighttime lights data are available for more years and for states beyond West Bengal. Below, I present evidence that political patronage using the electricity sector likely extends beyond West Bengal to other parts of the country, spanning multiple elections and political parties.

A. *Results Extend to Other States in India across Elections*

Figure 8 presents two panels: one showing a close-election RD for *actual* electricity consumption for all of India, as measured by nighttime lights. The right-hand-side panel shows the RD estimate by year relative to a state election—I include six years before and after each election. The graph shows results from elections across multiple states having elections in different years from 2009 to 2022. These patterns are consistent with what I find for West Bengal: no detectable discontinuities in electricity consumption before an election but a higher electricity consumption in assemblies aligned with the ruling party after. Table 4 shows the magnitude, indicating that electricity consumption is almost 0.48 log points higher in assemblies aligned with the ruling party.

from previous readings, there is discretion involved in the data entered. It is also widely acknowledged that MLAs hold a great deal of sway over local government authorities and, therefore, could potentially influence local billing centers. These billing centers are dispersed all over the state, but it is in narrowly aligned assemblies that we observe statistically significantly lower levels of reported consumption.

[14] "'Many people known to support the ruling party are allegedly involved in hooking and tapping,' a source said . . . . The chief minister had accused WBSEDCL of 'callousness' and questioned the efficacy of such [anti-theft] drives." *Telegraph*. 2014. "Power Theft Test for Mamata—State Utility to Seek CM's nod to Relaunch Crackdown." July 31.

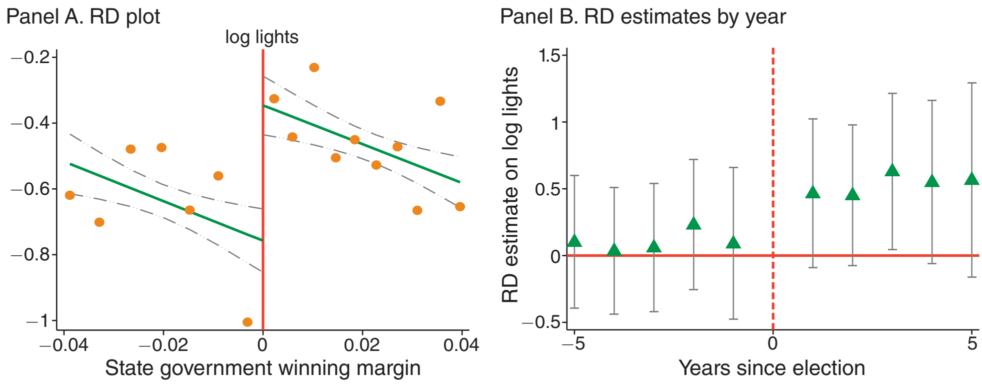

Figure 8. Higher Actual Electricity Consumption in Ruling Party Regions (All India, 2006–2022)

Notes: In panel A, I test for a discontinuity in log(nighttime lights) across assemblies that are aligned and not with the ruling party all across India from 2009 to 2022, using equation (1) at assembly level. I find that there is a discontinuously higher density of nighttime lights in assemblies just aligned with the ruling party after an election year. I use an optimal bandwidth of 4.17 pp. Panel B plots the RD estimates from equation (1) separately for each year, starting five years before an election to five years after an election, and finds a trend break after an election year, with selectively greater electricity consumption in areas where the ruling party narrowly won. Online Appendix Figure A10, panel B shows robustness of these results for a wide range of bandwidths from 2.5 to 7 pp. Standard errors clustered at the assembly level. This result is robust to other functional forms of nighttime lights, including levels (online Appendix Figure A14).

Table 4—Discontinuity in Actual Electricity Consumption (All India)

	log(*lights*) (1)	log(*lights*) (2)	log(*lights*) (3)	log(*lights*) (4)	log(*lights*) (5)	log(*lights*) (6)	log(*lights*) (7)
RD_Estimate	0.599 (0.158)	0.597 (0.149)	0.577 (0.141)	0.534 (0.132)	0.503 (0.124)	0.479 (0.118)	0.470 (0.113)
Observations	2,570	3,094	3,544	4,091	4,601	5,065	5,585
BW (win margin pp)	2.500	3	3.500	4	4.500	5	5.500

Notes: This table tests for a discontinuity in log(nighttime lights) across assemblies that are aligned with the ruling party versus not across India and presents the RD estimates from equation (1) for a range of seven bandwidths: 2.5 to 5.5 pp vote margin. The bandwidth of 4 pp closely approximates the optimal bandwidth, which has been used consistently across all billing and night-lights outcomes. This table shows evidence of discontinuously higher actual electricity consumption across India after an election year, from 2009 to 2022. Online Appendix Figure A10 shows robustness of these results for a wider range of bandwidths. Standard errors in parentheses clustered at the assembly level.

B. *Lagged Effects of Previous Ruling Party*

The billing data begin in 2011 and cannot be used to examine the aftermath of the 2006 elections. But, in 2012, Figure 9 shows suggestive evidence that the CPI(M) (ruling party after the 2006 elections) engaged in the same form of electricity underreporting in the assemblies they won in 2006. Immediately after the 2011 elections, when the AITC defeated CPI(M), there is evidence of consumption underreporting in CPI(M)-controlled assemblies. However, as shown in Table 5, this effect gets smaller and smaller and by 2015 is no longer statistically distinguishable from zero when the AITC has established itself and has set up its own machinery to underreport its constituents' electricity consumption.

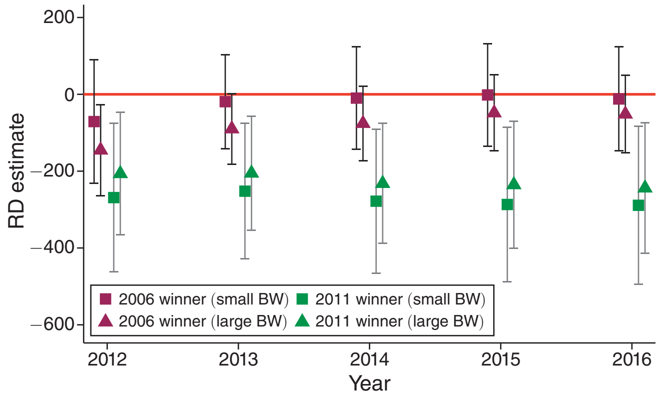

FIGURE 9. STUDYING DISCONTINUITIES IN REPORTED CONSUMPTION USING THE WINNING AND LOSING ASSEMBLIES FROM THE 2006 ELECTION

Notes: I test for discontinuities in the reported consumption in assemblies aligned or not with the ruling party that won the 2006 election (CPI(M) or the 2006 winner) and the 2011 election (AITC or the 2011 winner), using equation (3) for each election-year. The running variable for the 2006 election results is defined as the number of winning votes (in addition to controlling for the total number of valid votes in each assembly) on the basis of legislative assemblies from the 2006 election, and the running variable for the 2011 election results is defined as the winning vote margin on the basis of legislative assemblies from the 2011 election, where the AITC party won. However, while the running variables are created from different elections, we examine the individual-level outcomes for electricity post-2011. This shows that while the previous ruling party may have been engaging in the same corrupt subsidization practices in their electoral term, their ability to do the same in the electoral term of a new ruling party is limited. The results shown include multiple bandwidths (BW 4,500 votes to 8,500 votes, with the RD estimate for the optimal bandwidth of 6,500 votes lying in between the two).

C. *Heterogeneity Analysis*

I study different sets of states to understand the patterns in discontinuously higher electricity consumption in some places and not others. First, using Pargal and Banerjee (2014), I pick the three worst and best-performing states in terms of utility distribution revenue losses. The three worst-performing states in this regard in 2010–2011 were Bihar, Manipur, and Odisha, with the highest losses, and the best-performing states were Chhattisgarh, Karnataka, and Andhra Pradesh. Following the RD design in Table 4, I separately estimate the RD coefficient for these two sets of states in columns 1 and 2 of Table 6. I find that there are higher discontinuities (statistically significant) across the RD cutoff in states with higher distribution losses. This appears consistent with a narrative that there are higher losses to electricity utilities in states where there is more corruption (or states with higher losses may have a lower cost of corruption).

Recent work shows that states with single electricity distributors provide more reliable electricity and are better at revenue collection compared to states with multiple electricity distributors (Mahadevan 2022). I examine whether there is discontinuously more electricity consumption in ruling party–aligned assemblies in states with single or multiple electricity distributors. I find in columns 3 and 4 of Table 6 that there is a large discontinuity in states with multiple distributors, which to a large degree is consistent with what Mahadevan (2022) finds. States with multiple distributors struggle to meet the electricity demand of firms and perform poorly in revenue collection—perhaps this opens up the demand for more

Table 5—Discontinuity in Reported Electricity Consumption (West Bengal–Two elections)

	West Bengal 2012 reported cons. of electricity (1)	West Bengal 2013 reported cons. of electricity (2)	West Bengal 2014 reported cons. of electricity (3)	West Bengal 2015 reported cons. of electricity (4)	West Bengal 2016 reported cons. of electricity (5)
Panel A. Post-2011 election, ruling party: AITC					
RD_Estimate	−223.110	−224.028	−250.721	−256.323	−261.015
	(81.806)	(76.032)	(80.781)	(85.367)	(87.853)
Observations	12,515	15,818	15,726	15,538	15,418
BW	6,500	6,500	6,500	6,500	6,500
Panel B. Post-2006 election, ruling party: CPI(M)					
RD_Estimate	−123.179	−92.568	−91.589	−62.912	−58.420
	(46.462)	(38.461)	(41.036)	(41.622)	(42.364)
Observations	11,152	16,053	15,834	15,820	15,695
BW	6,500	6,500	6,500	6,500	6,500

Notes: This table tests for discontinuities in the reported consumption in assemblies aligned or not with the ruling party that won the 2006 election (CPI(M) or the 2006 winner) and the 2011 election (AITC or the 2011 winner), using equation (3) for each election-year. The running variable for the 2006 election results is defined as the number of winning votes (in addition to controlling for the total number of valid votes in each assembly) on the basis of legislative assemblies from the 2006 election, and the running variable for the 2011 election results is defined as the winning vote margin on the basis of legislative assemblies from the 2011 election, where the AITC party won. However, while the running variables are created from different elections, we examine the individual-level outcomes for electricity post-2011. This shows that while the previous ruling party may have been engaging in the same corrupt subsidization practices in their electoral term, their ability to do the same in the electoral term of a new ruling party is limited. The results are shown for the optimal bandwidth of 6,500 votes (approximately equivalent to 4.17 pp).

Table 6—Discontinuity in Actual Electricity Consumption—Comparing Sets of States with Single and Multiple Electricity Distributors, High and Low Revenue Losses from Distribution, and Good and Bad Ratings

VARIABLES	Low dist. losses log(lights) (1)	High dist. losses log(lights) (2)	Single discom log(lights) (3)	Multiple discoms log(lights) (4)	Worst utilities log(lights) (5)	Best utilities log(lights) (6)
RD_Estimate	0.373	1.994	−0.104	0.419	0.327	0.106
	(0.095)	(0.211)	(0.091)	(0.099)	(0.121)	(0.115)
Observations	9,690	3,273	9,574	25,780	11,289	4,158

Notes: This table tests for discontinuities in actual electricity consumption in assemblies just aligned with the ruling versus not but studies the heterogeneity in this RD estimate across different sets of Indian states. The regression follows the estimation equation (1), while restricting the sample to the following subsets of states. In all cases, the optimal bandwidth of 4.17 pp is used. Using Pargal and Banerjee (2014), I find sets of states that had the lowest and highest reported financial losses in their electricity sector (columns 1 and 2 showing distribution level losses) and sets of states that had a single electricity provider in the state or multiple in columns 3 and 4. Finally, using ratings assigned by the Ministry of Power (2019) based on a range of characteristics like finances, complaints files, and audits required, I assign state electricity utilities that received a grade of A+ to the list of best-performing states and those that received a grade of C into the worst utilities (columns 5 and 6). Standard errors in parentheses clustered at the feeder level.

electricity or preferential access, which politicians can take advantage of by favoring their allies. One of the hypotheses discussed in Mahadevan (2022) argues that states with multiple distributors suffer from coordination failures that lead to low revenue collection and poor supply. It is possible that the same reason also makes them more susceptible to corruption.

Finally, using ratings assigned by the Ministry of Power (2019) based on a range of characteristics like finances, complaints files, and audits required, I assign state electricity utilities that received a grade of A+ to the list of states with the best performance (Karnataka, Gujarat, and Uttarakhand), and those that received a grade of C to the worst utilities (Manipur, Meghalaya, Tripura, Uttar Pradesh, and Madhya Pradesh). In columns 5 and 6 of Table 6, I show that there is a large, statistically significant discontinuity in electricity access in the states with the worst-rated utilities, while there is a smaller, statistically insignificant effect in states with the best-rated utilities. These results suggest that greater accountability in the functioning of utilities may deter the capture of utilities for political corruption. A major component of the Annual Integrated Ratings of State Discoms (the ratings I use to define the worst- and best-managed utilities) is "performance excellence," which includes the items billing efficiency, collection efficiency, distribution loss, and corporate governance. Weakness in any of these measures would be consistent with vulnerabilities that allow political patronage to occur, particularly through weak billing institutions. Rating high on these four measures would similarly imply the strength of the electricity utility against manipulation by politicians who have a strong hold over local billing centers. High-rated state utilities are also more likely to employ the "use of digital channels for billing and payments and running special programs to improve awareness and engagement in rural areas," which would once again limit the ability of local politicians to exploit the manual entry of consumption to provide subsidies to their voters.[15] One of the high-rated utilities has very recently implemented an "AI-based app that can autofill units consumed in discom bills. Bills are generated based on images captured by meter readers, so no manual overriding is possible" (Ministry of Power, Government of India 2022, p. 41). These measures of highly ranked discoms certainly explain how it would be hard for local politicians to push for a misreporting of consumption on bills, explaining why we do not observe a discontinuously lower reported consumption in states that were ranked with an A+ grade.

D. *Robustness Checks*

In online Appendix Section D, I discuss a range of robustness checks that validate the results in this paper. The RD estimates for a range of billing and lights outcomes are robust to both smaller and larger bandwidths (online Appendix Sections D.2, D.3, and D.4). While I present the main results from the administrative data clustering at the electricity feeder level (the level at which electricity supply is highly correlated and governed by a single customer care center), I also show robustness to clustering at the assembly level (online Appendix Section D.5). I show the main results for all major consumer categories, but there may be an argument to be made that agricultural consumers are unique given the already large subsidies they receive and their use of electricity primarily for irrigation (not visible using nighttime lights). Therefore, I show that the main results remain robust to dropping agricultural consumers, who

[15] Tenth Annual Integrated Ratings and Ranking 2022 (Ministry of Power, Government of India 2022, p. 5).

comprise about 1.5 percent of the consumer base (online Appendix Section D.6). I show that the results using nighttime lights remain robust to using levels instead of the commonly used log transformation (online Appendix Section D.7).

VI. Welfare Consequences of Political Patronage

The electricity context sets itself apart from other instances of corruption by allowing for a full accounting of the economic costs involved. The combination of administrative data from the ground and satellite data to describe the full picture is key to not only detecting corruption but also identifying the welfare consequences. The corruption described in this paper would not be problematic from an efficiency perspective if it involved merely a transfer from one group to another. However, the distortions in electricity billing lead to a deadweight loss that outweighs gains to any group, which makes this form of patronage costly. In this section, I describe how the paper quantifies welfare costs.

This paper characterizes the underreporting in billing data as providing an informal subsidy to constituents of the ruling party, described in Figure 10. Under the existing electricity price structure, the average price charged for electricity would be $AP_{initial}$. As a consequence of political patronage, consumers in assemblies of the ruling party effectively face a lower average price of AP_{final}. Figure 10 describes the loss in producer profits, gain in consumer surplus, and deadweight loss to society as a result of the informal subsidies provided by politicians to their constituents. In order to estimate the change in producer profits, I use a combination of the overconsumption of electricity in response to the subsidy from Table 1 and the implicit price subsidy conferred by the underreporting of consumption. Similarly, I compute the gain in consumer surplus to favored constituents using the effective change in prices from the subsidy ($AP_{initial} - AP_{final}$), a measure of demand elasticity, and the final quantity consumed by favored constituents Q_{final}. I provide details of these calculations in Tables 7 and 8. Importantly, how each parameter in Figure 10 is calculated is explained in detail in online Appendix Table A10.

The difference between the changes in producer and consumer surplus provides the deadweight loss to society. However, as is evident from Figure 10, the change in consumer surplus depends on the price elasticity of demand for electricity, to infer the effective increase in quantity consumed by beneficiaries of the subsidy. Therefore, I first estimate the price elasticities of demand across consumer categories and arrive at a weighted mean elasticity for the total sample.

However, estimating the price elasticities of demand from the consumption data is not straightforward, given the data manipulation. I, therefore, develop a method of deriving elasticities that accounts for anomalies. As the *first step*, I select assemblies where I statistically reject that the data are manipulated (described in online Appendix Section E). I then compute elasticities for each assembly and consumer category for this subsample using an instrumental variable approach that leverages exogenous variation in policy-led tariff changes over time (online Appendix Section E.1). The *second step* involves building a predictive model for elasticities in assemblies with no manipulation (online Appendix Section E.2). In the *third step*, the paper predicts elasticities for the remaining assemblies where there is evidence of data manipulation (details described in online Appendix Section E.3). The result is a

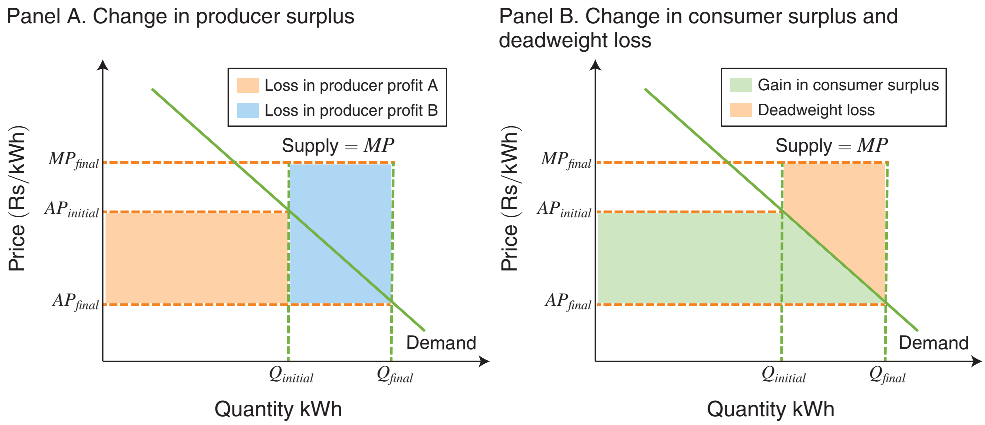

FIGURE 10. CHANGES IN PRODUCER AND CONSUMER SURPLUS ACROSS CONSUMER GROUPS

Notes: These figures show the changes in producer surplus and consumer surplus arising from politically motivated electricity subsidies offered to constituents of the ruling party in West Bengal. I simplify the indirect subsidies by politicians through underreporting in billed data by assuming an average level of electricity subsidy for all electricity consumers in regions aligned with the ruling party. The parameters $Q_{initial}$ and $AP_{initial}$ represent the electricity quantity consumed and average price paid by constituents who did not benefit from the subsidy, while Q_{final} and AP_{final} represent the same for constituents of the ruling party whose billed consumption was underreported. MP_{final} represents the price the electricity utility charges for the marginal unit in the range between $Q_{initial}$ and Q_{final}, as observed from the published tariff schedule of the utility for the year 2014. For simplicity, this figure does not show the entire MP schedule (that can be seen in online Appendix Figure A16 for different years and consumer categories). This figure focuses on the subsection of the MP curve that is relevant to determining utility revenues for the change in quantity consumed from $Q_{initial}$ to Q_{final}. The shaded areas show the loss in producer profit, gain in consumer surplus, and overall deadweight loss. They are also drawn to scale for each consumer category, with each of the parameter values based on measurements and estimations from the analysis in this paper (online Appendix Figure A17). The source of each parameter is discussed in Table 7 and online Appendix Table A10.

unique estimate for elasticity for four consumer groups in each assembly in the dataset (online Appendix Table A8). The advantage of this method over previous estimates of price elasticities using aggregated billing data is that the individual-level billing data allow for better identification.

The *final step* uses a weighted mean of the predicted elasticities to calculate the consumer surplus and producer loss for each consumer class as a result of the informal subsidy provided by politicians. The elasticity estimates I compute advance the literature by updating the residential and commercial (both urban and rural) elasticity estimates that were in use before (Saha and Bhattacharya 2018). My estimates are within the range of prior work for residential consumers but are significantly higher for commercial accounts. I argue that prior estimates used aggregate data that may conceal problems such as data manipulation. But correcting for manipulation in my estimates, I arrive at figures that may be more reflective of what firms report: having to frequently use generators and taking advantage of being able to switch in response to high marginal prices of electricity. This nuance is somewhat masked when looking at weighted mean elasticities because the weighted mean estimate in this paper (Table 7) of −0.60 is virtually identical to the weighted mean estimate from Saha and Bhattacharya (2018), whose figure is −0.61. Further, it is easy to infer from Figure 10 and online Appendix Figure A17 how changes in producer and consumer surplus, and deadweight loss would respond to other estimates of elasticity. Online Appendix Figure A18 depicts how

Table 7—Calculations for Welfare Analysis in Figure 10

	Variable	Residential urban	Commercial urban	Residential rural	Source
Calculation of $AP_{initial}$	Average price faced by assemblies who do not receive the subsidy				
Base kWh consumed	$Q_{initial}$	752	1,055	279	Mean kWh in RD bandwidth below cutoff
Total bill for base kWh	$bill\_Q_{initial}$	4,544	6,344	1,427	$Q_{initial} \times$ tariff schedule from utility
Initial average price (Rs)	$AP_{initial}$	6.04	6.01	5.11	$bill\_Q_{initial}/Q_{initial}$
Calculation of AP_{final}	Average price faced by assemblies who receive the subsidy				
Underreporting	RD_est_1	−408	−636	−140	RD estimate from Table 2
Reported consumption	$Q_{reported}$	344	419	139	$Q_{initial} + RD\_est\_1$
Overconsumption from lights	RD_est_2	0.53	0.53	0.53	RD estimate from Table 1
log(*cons*)–log(*lights*) multiplier	Multiplier	0.10	0.07	0.15	Regression coeff. from online App. Figure A6
Reported bill	*bill_reported*	1,872	2,662	646	$Q_{reported} \times$ tariff schedule from utility
Estimated overconsumption (lights)	Q_{lights}	793	1,093	302	$\exp\{\log(Q_{initial}) + (RD\_est\_2 \times \text{multiplier})\}$
Final average price (Rs)	AP_{final}	2.36	2.44	2.14	$bill\_reported/Q_{lights}$
Calculation of MP_{final}	Marginal price of overconsumed units from utility price tier corresponding to $Q_{initial}$ to Q_{final}				
Final marginal price (Rs)	MP_{final}	6.60	8.12	5.84	MP for price tier corresponding to $Q_{initial}$
Calculation of Q_{final}	Calculation of electricity consumption by constituents who receive the subsidy				
Weighted elasticity estimate	*elas_weighted*	−0.60	−0.60	−0.60	Weighted mean of elasticities (Online App. Table A6)
Change in log(kWh) from subsidy	$\delta_{\log q}$	0.56	0.54	0.52	$[\log(AP_{final}) - \log(AP_{initial})] \times elas\_weighted$
Change in kWh	δ_q	421	568	145	$\delta_{\log q} \times Q_{initial}$ (approximation)
Final kWh consumed	Q_{final}	1,173	1,623	424	$Q_{initial} + \delta_q$

Notes: This table shows the steps involved in deriving the parameters used for the welfare analysis in Table 8. Some of the parameters are sourced from reduced-form estimations in the paper, with the relevant regression tables cited. Other parameters are derived from direct measurement in billing or nighttime lights datasets used in the analysis, as well as statistics and prices determined by the electricity utility. These sources are cited where appropriate, and the calculations involved in arriving at each of the parameters in online Appendix Figure A17 are detailed in the table above.

welfare values respond to changes in elasticity, showing that deadweight loss increases monotonically with higher elasticity.

Costs and Benefits of the Manipulation of Electricity Bills.—The underreporting of consumption in bills leads to large welfare distortions not only for the electricity producer and the consumers involved but also more widely for the economy. The combination of the implicit subsidy imposed by consumption underreporting and

TABLE 8—FINAL CALCULATIONS FOR LOSS IN PRODUCER PROFIT AND GAIN IN CONSUMER SURPLUS FOR FIGURE 10

	Variable	Residential urban	Commercial urban	Residential rural	Source
Number of accounts (mill.)	*num_acc*	6.88	1.25	5.06	Utility annual report 2014
Producer profit loss A	*prod_A*	2,769	3,774	829	Area of A in Fig A17: $Q_{initial} \times (AP_{final} - AP_{initial})$
Producer profit loss B	*prod_B*	1,785	3,226	606	Area of B in Fig A17: $(\Delta Q) \times (MP_{final} - AP_{final})$
Total producer loss	*prod_surplus*	31,338	8,718	7,263	$(prod\_A + prod\_B) \times num\_acc$
Producer loss (US$/term)	*prod_surplus_$*	2,346	653	544	US$ value for 5-yr electoral term (Rs 66.79/US$)
Gain in consumer surplus	*cons_surplus*	24,389	5,965	5,285	$0.5 \times (Q_{initial} + Q_{final}) \times (AP_{final} - AP_{initial}) \times num\_acc$
Consumer gain (US$/term)	*cons_surplus_$*	1,826	447	396	US$ value for 5-yr electoral term (Rs 66.79/US$)
Total producer loss mill. US$/term		3,542			
Total consumer gain mill. US$/term		2,668			
Deadweight loss mill. US$/term		875			

	Bootstrapped mean	**Bootstrapped SE**	**L 95 percent conf. interval**	**R 95 percent conf. interval**
Total producer loss mill. US$/term	3,532	96.53	3,343.07	3,721.48
Total consumer gain mill. US$/term	2,668	65.69	2,539.53	2,797.02
Deadweight loss mill. US$/term	864	37.11	791.27	936.74

Notes: This table shows the steps involved in arriving at estimates for the changes in producer surplus and consumer surplus as a result of receiving a politically motivated electricity subsidy. Table 7 shows how each of the parameters used in this table are defined. Figure 10 and online Appendix Figure A17 indicate the areas of the graphs that contribute to changes in the producer and consumer surplus (PS and CS). Once each of the parameters plotted in the graphs is derived, the calculations of the PS and CS may be simplified to computing the areas marked in the graph. The figures for the number of accounts in each consumer category used in this table (num_acc) are a combination of numbers published by the utility (16.5 million consumer accounts in 2014) and author calculations from the billing data on the share of accounts that are residential urban, commercial urban, and residential rural in ruling party–controlled assemblies. These shares are then multiplied with the total consumer base of 16.5 million accounts to arrive at consumer category specific numbers for the selected assemblies. I use 2014 here as a representative year that falls in the middle of my analysis period of 2011–2016. Finally, I bootstrap estimates of $Q_{initial}$, $AP_{initial}$, underreporting of consumption (RD_est_1), overconsumption of electricity measured by nighttime lights (RD_est_2), and the $\log(cons) - \log(lights)$ multiplier using a 1,000 draws with replacement, and find bootstrapped estimates of total producer loss, total consumer gain, and deadweight loss.

the satellite data to identify overconsumption in the same regions leads to a loss of US$3.5 billion in electricity producer profits in West Bengal in a single electoral term (Table 8). My results demonstrate that there is a likelihood that this form of corruption extends to other states (Figure 8), likely pegging the losses to electricity producers magnitudes higher. Conversely, the gains to consumers stand at US$2.7 billion. As a result, the efficiency loss amounts to US$0.9 billion.

Finally, Table 8 also presents bootstrapped estimates of welfare, providing a 95 percent confidence interval for deadweight loss of US$0.80 to US$0.94 billion. I bootstrap estimates of $Q_{initial}$, $AP_{initial}$, underreporting of consumption (RD_est_1), overconsumption of electricity measured by nighttime lights (RD_est_2) and the log(-*cons*) − log(*lights*) multiplier using a 1,000 draws with replacement and find bootstrapped estimates of total producer loss, total consumer gain, and deadweight loss.

I also benchmark the welfare estimates using elasticities from prior work (Saha and Bhattacharya 2018). Online Appendix Tables A11 and A12 show the analogous calculations from Tables 7 and 8 using the weighted mean of elasticity estimates in Saha and Bhattacharya (2018).

Tables 7 and 8 present welfare estimates based on the assumption that underreporting of electricity consumption takes place at some level in all ruling party–controlled assemblies. One reason to support this assumption is that the scale of losses implied seems in line with what Denyer (2012) estimates for the annual financial losses for Indian electricity utilities in 2012: US$46 billion. The loss in producer profits in this paper for a 5-year period is US$3.5 billion, or US$0.7 billion annually. Given that West Bengal contributes to about 6 percent of the national population, this implies a net financial loss of over US$2.8 billion annually, which is almost 4 times the estimate in the paper.[16] Nevertheless, it is a useful exercise to estimate a lower bound for the welfare figures based on the assumption that underreporting strictly occurs in ruling party assemblies involved in close elections (or, more accurately, within the RD bandwidth for which we still estimate significant effects). Online Appendix Table A13 now presents these estimates and finds a deadweight loss of US$178 million if we assume that underreporting happens only in ruling party assemblies with a 7 pp vote share bandwidth.

VII. Conclusion

This paper demonstrates that political patronage can have adverse welfare implications that go well beyond the transfers caused by selective access to a few favored groups and imposes a significant efficiency loss for society. An innovation in this paper is to use a combination of administrative billing data for 72 million electricity customers with satellite data to draw a distinction between measured electricity consumption and actual consumption. I present evidence that politicians favor their voters both in terms of providing electricity access and in subsidizing them by underreporting their billed consumption. Consistent with the hypothesis that political agents may influence intermediaries to manipulate the data, I find that in assemblies where the ruling party narrowly won, there are greater anomalies in the consumption distribution. This demonstrates evidence of politically motivated data manipulation and isolates the methods used to carry it out. Both of these elements help me capture the impact of political manipulation on electricity providers and consumers. Understanding the effects on net welfare is a particular contribution of

[16] Of course, there are several other contributors to financial losses by utilities, including technical and infrastructure related, other forms of theft, and undercollection of bills.

this work, as unlike other settings studied in the literature, the electricity setting is unique in its ability to allow for a full accounting of gains and losses.

I calculate a total deadweight loss as US$0.9 billion. These numbers represent estimates for a single Indian state but could be larger if scaled to include other Indian states that have similar vulnerabilities to political manipulation. Targeted voters in assemblies aligned with the ruling party may benefit from cheaper electricity, but the loss in profits for the electricity provider, in particular, has wide-ranging implications. Losses in electricity producer profits disadvantage *all* consumers, even those whom the politicians sought to favor. Losses hurt the ability of utilities to meet electricity demand, resulting in poor quality and unreliable supply for all consumers (Burgess et al. 2020). If funds used to bail out the utilities cut into the government's developmental budgets, then bailouts may be detrimental to poorer sections of society and have wide-ranging welfare consequences. Indeed, the bailout of electricity utilities in India has been virtually systematized by the setup of a centralized bailout fund through the Ujwal DISCOM Assurance Yojana (Chatterjee 2017, 2018). Further, increased outages and unreliable electricity that result from insufficient revenue have implications for growth and productivity (Fried and Lagakos 2023; Allcott, Collard-Wexler, and O'Connell 2016). Interestingly, the same bailout scheme that allows these corrupt practices to continue also places limits on the scale of these practices, as there will be additional scrutiny on a state that registers higher-than-normal losses. This paper argues that that may be one reason these practices remain more confined to an incumbent party. While research on manipulation in administrative data has explored anomalies arising from measurement error, misreporting by consumers, insufficient incentives for data collectors, and eligibility manipulation, the possibility of politically motivated manipulation remains less explored (Slemrod 2016; Camacho and Conover 2011). Given its large impact on policymaking, ability to provide public goods, and measurement of development progress, this is an important area for future study.

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