Paying for power

Fiona Burlig and Anant Sudarshan*

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Abstract

Developing countries struggle to collect public revenue, reducing their ability to provide services. In the Indian electricity sector, state-run utilities incur billions of dollars in losses, exceeding the budgets of other ministries, because they do not collect on payments due to them. This paper reports the results of an enforcement experiment run in partnership with two state utilities in Madhya Pradesh, where only 28 percent of domestic customers pay in full. We randomize 30,000 households into a control group and several enforcement treatment arms. We find that mailed disconnection notices and electricity disconnections significantly reduce arrears in the short-run. In contrast, an identical notice delivered in person by local utility staff has no effect, as does a traditional SMS reminder and a social comparison nudge. We see evidence of significant heterogeneity in treatment effects based on observable characteristics, suggesting targeting may be effective.

Key words: Enforcement; bill non-payment; electricity
JEL Codes: O13; Q48; H26

*Burlig: Harris School of Public Policy and Energy Policy Institute (EPIC), University of Chicago, and NBER. Email: burlig@uchicago.edu. Mailing address: Keller Center, 1307 E 60th St., Chicago, IL 60637. Sudarshan: Department of Economics, University of Warwick. Email: anant.sudarshan@warwick.ac.uk. Mailing address: S2.92 Social Sciences, University of Warwick, CV47AL. We thank Susanna Berkouwer, Manasi Deshpande, Koichiro Ito, Ryan Kellogg, Mushfiq Mobarak, Peter Ganong, Michael Greenstone, Catherine Wolfram, and seminar participants at the Coase Conference, Midwest Energy Fest and UC Energy Camp for helpful comments and suggestions. We gratefully acknowledge financial support from the Oak Foundation and the Griffin Applied Economics Incubator. Kabir Nagadia, Abhishek Deshwal, Animesh Jayant, Simran Kalra, Garrison Schlauch, Anjaney Singh, and Rathan Sudheer provided excellent research assistance. All remaining errors are our own. This project received IRB approval from the University of Chicago (Protocol No. IRB20-2127), and is registered on the AEA RCT registry (Identification No. AEARCTR-0008742).

1 Introduction

There are no examples of countries that have grown substantially richer without also consuming more energy. The strikingly strong empirical association between energy use per capita and measures of national wealth gives rise to two crucial questions. First, what is the *causal* relationship between energy consumption and measures of developmentment? Second, why have developing countries persistently struggled to provide access to reliable electricity to their populations, and how might we fix this problem?

Although a growing body of research has sought to document the causal impact of modern energy on welfare[1], the second question remains less well understood. Burgess et al. (2020) document the persistently large difference in reliable electricity access between developed and developing countries. They argue that one reason it has been difficult to bridge this gap is that electricity utilities in poorer countries find themselves trapped in a low-quality, low-payment equilibrium. Simply put, consumers frequently do not pay for the power they consume, which means that utilities cannot recover their costs, and are forced to ration supply and reduce quality. In these settings, electricity distribution becomes a largely state-run affair with bankrupt utilities that are under-staffed and under-resourced.

This diagnosis is the point of departure for the present paper. Our setting is the state of Madhya Pradesh, one of the largest states in India, with an estimated population in 2020 of over 85 million. It is also one of the poorer parts of the country, with a state GDP per capita of just 1,500 USD in 2019-20 (about three-fourth of the India average). Madhya Pradesh exemplifies the equilibrium we have just described. In 2020, the two state-run utilities we worked with in Madhya Pradesh were recovering only 70 percent of the price of power they

1. A number of papers have sought to identify a causal link between electricity and improvements in development outcomes (e.g. Dinkelman (2011), Lipscomb, Mobarak, and Barham (2013), and Allcott, Collard-Wexler, and O'Connell (2016)), modulated by recent evidence showing significant heterogeneity in the returns to electrification (Lee, Miguel, and Wolfram (2020), Burlig and Preonas (n.d.)).

supplied.[2] Meanwhile the average hours of supply in rural Madhya Pradesh was just 20 hours.

The costs of not being able to pay for electricity go well beyond damaging the state's ability to supply power. In countries like India, electricity distribution losses are a now a substantial burden on the state exchequer. To understand the scale of the problem, consider that the annual budget of India's Health Ministry in 2018-19 was about USD 7.5 billion (at Jan 2019 exchange rates). In that same year, distribution company losses across the country were as high as USD 12.4 billion. In Madhya Pradesh the corresponding pair of numbers were about USD 1.09 billion against USD 1.43 billion. These losses do not include the cost of explicit payments from the state exchequer to utilities to support tariff subsidies, and therefore reflect costs that should have been recouped from consumers but were not. This debt is periodically shifted to state and central budgets in order to protect utilities from bankruptcy.

Increasing revenue recovery is therefore critical both to improving electricity supply and to freeing up resources for spending in other areas. In this paper we report early results from an experiment designed to test the impact of several enforcement measures available to the these utilities on consumer payment behavior, arrears, electricity consumption, and household welfare outcomes and attitudes towards electricity payment. We carry out this experiment in partnership with the Madhya Pradesh Eastern Zone (MPEZ) and Madhya Pradesh Central Zone (MPCZ) utilities of Madhya Pradesh, in two service regions of the state, each serving about 4.6 and 3.5 million domestic consumers respectively.[3] The experiment covers 30,000 domestic consumers, who were randomly assigned to either a control group or to one of several treatments: (i) SMS reminders, (ii) SMS reminders paired with a social comparison 'nudge', (iii) Formal notices warning of impending disconnection under

2. This number captures utility under-performance but if anything underestimates the full extent of the payment gap because part of the cost of power is paid by the state government directly to utilities, to enable them to set subsidized tariffs.

3. The revenue recovery problem is severe for households but not restricted to them. However, in this paper we do not study commercial, agricultural, or industrial consumers.

the law, and (iv) electricity disconnections following a formal notice. We describe the design in more detail in Section 1.

In principle, the enforcement problem these electricity distribution companies face may appear the same as that for any private utility anywhere in the world. That is to say, their job is to monitor consumption using meters, deliver bills, and collect on dues. The set of legal options available to the utility to encourage payment are also standard. The primary incentives for consumers to comply are to avoid late fees and the threat of disconnection, possibly combined with further legal action.

What complicates matters in developing country settings is the remarkably high baseline level of non-payment and electricity theft. Using billing data from the Madhya Pradesh utilities we find that only 28 percent of consumers pay in full each month. Table 1 shows the distribution of the share of monthly amounts owed that are paid by consumers, underscoring the rampant nature of underpayment. This outcome is made worse by a combination of low state-capacity on the part of the payment collector (the state-run utility) and by a political narrative that has treated electricity as a right rather than a commodity that must be bought and sold.[4]

When non-payment is widespread, enforcement levers such as disconnection become difficult to use as a matter of rule. For utilities in Madhya Pradesh, billing data suggests that disconnecting households who have carried unpaid arrears for three months would imply cutting off 50 percent of their consumer base. This would be politically infeasible, operationally expensive, and perhaps even economically inefficient if household decision-makers do not internalize positive externalities and long-run benefits from electricity consumption.

Furthermore, once non-payment becomes a social norm (Burgess et al. (2020)), it is uncertain how consumers might respond to reminders, warnings, or late fees — the other

4. As a recent example, on March 15, 2022, the Chief Minister of Madhya Pradesh announced in the state assembly that the government would waive arrears for about 8.8 million domestic consumers, the second such announcement in two years. Indeed the government went further, also announcing that they would *refund* bill payments already made by some consumers as part of a prior settlement scheme so that they do not feel 'cheated' by the new announcement.

tools available to most utilities.[5] Indeed, even households that do get disconnected may respond by illegally reconnecting themselves to the grid, a form of theft that is commonplace in settings such as India but very rare in most developed countries.

We report three early findings from our experiment in this paper. First, we find that consumers can be induced to pay more, even in the context of a social norm of widespread non-payment. We tested the effect of mailing customers formal notices, warning them that non-payment is a criminal offense and that continued non-payment attracts the possibility of electricity disconnection. We found that households who received these letters reduced their arrears approximately 8 percent (INR 287 in one utility and INR 157 in the second).

Similarly we found that consumers who did not pay off arrears in response to such notices, nevertheless make additional payments when visited by technical staff charged with carrying out a disconnection unless an immediate spot payment of at least 50 percent of dues is made. After such visits, average arrears for consumers in the disconnection treatment were 7.9 and 8.7 percent lower than the control in the two utilities. Coville et al. (2021) also find that disconnections improve payments in the context of new water connections in Nairobi, Kenya. In contrast, our study takes place in the two large Indian utilities where non-payment norms have been entrenched for years, and where electricity losses are a significant drain on the state's finances.

Our second result relates to process. We find that consumers respond to warning notices as described above only when they are delivered through registered post from the utility head office. An identically worded letter, when provided to local utility linesmen to deliver to customers in-person, has no impact on arrears.

We interpret this finding as revealing how the priors that citizens place on the incentives of different state actors affects the credibility of promises (or threats) made by them. In our setting linesmen from the local utility office are known to consumers. They may also be plausibly aware of whether consumers are in good standing and are also responsible for

5. Jack and Smith (2020) show that pre-paid electricity meters can reduce utility losses. However, these infrastructure upgrades are costly, and rarely used in India.

carrying out disconnections. In a setting where enforcement by local utility staff is seen as being lax, using them as messengers may undercut the credibility of any warnings they deliver.

Lax enforcement may occur for multiple reasons. Local staff may turn a blind eye to violations; they may take bribes and engage in side deals with households; or disconnections may simply be too infrequent for households to believe that such an action is likely. Whatever the cause, it seems to be the case that households do not pay attention to warnings delivered by linesmen. It is possible that these staff also verbally undermine the letters they carry but unfortunately we do not have visibility into the nature of their interaction with consumers at the point of delivery.

There exists a growing literature describing the incentives governing public sector employees and studying how to change them in ways that improve performance (Finan, Olken, and Pande (2017)). An alternative to aligning agent incentives with tasks, is to re-assign tasks to those agents of the state whose existing contracts provide the most appropriate incentives. The field staff of state utilities may have rent-seeking opportunities but no direct stake in utility profits. Conversely a senior bureaucrat leading a state-wide enforcement campaign may be unable to extract rents from individual consumers, but may see career benefits from improving the performance of utilities under their management.[6] If consumers understand these differences and use the delivery mode of the letter to infer which part of the state apparatus is 'in charge', they may respond differently to the same message depending on how it is delivered.

Our third finding is a null effect. We find that nudges and reminders delivered through SMS messages have no impact on payments. Reminders and behavioral nudges have been used to increase tax payments, with mixed results (e.g. Neve et al. (2021), Holz et al. (2020)). Peer comparisons have previously been found to influence consumer energy use behaviors in

6. Banerjee (1997) provides an early theoretical discussion of the incentives of different agents of the state. Bertrand et al. (2019) finds that the prospect of promotion to senior ranks significantly influences bureacrat effort.

both developed and developing countries (Allcott and Rogers (2014)). These results do not seem to translate to the thorny challenge of getting people to pay their bills.

In future work as part of this project we intend to study longer-term payment outcomes. We will also combine utility administrative data with a planned household survey in both treatment and control groups to determine whether paying more to the utility has impacts on other measures of household welfare such as changes in food or health expenditures, and investigate whether household attitudes to the utility change once they are exposed to an enforcement action and attempt to measure informal payments or bribes they may have paid to local utility staff.

Finally, we will explore how best to target different enforcement strategies, in a setting where utility resources are limited, the costs of disconnections are meaningful, and where consumers may respond in different ways to different strategies.

2 Data

We collect outcome data from two sources: administrative data from the distribution company and household surveys conducted over the phone. In this paper we discuss results using administrative data only.[7]

Households receive electricity bills on a monthly billing cycle and the utility made available a monthly panel of consumer records including at least 6 months of pre-period data for each experiment household. Administrative data collection remains ongoing and will eventually extend to at least 6 months of post-period data.

The primary outcome variable of interest in the billing data is the utility measure of arrears, which is the difference between cumulative monthly billed charges and consumer payments, net of any waivers, late fees, fixed charges and so on. The billing data also

7. We conducted our baseline survey over the phone in December 2021; the endline survey will take place in fall 2022.

provides records of household consumption allowing us to measure whether enforcement actions induce changes in both arrears and consumption behaviors.

Finally, the utility maintains a separate dataset containing records of consumer payments, and we were given access to a monthly aggregated version of this dataset. We do not observe each payment made by the consumer separately, but we do observe the total amount credited as being paid in each month.

Before describing the empirical approach we take to analyze the experimental sample, we summarize two stylized facts from administrative data.

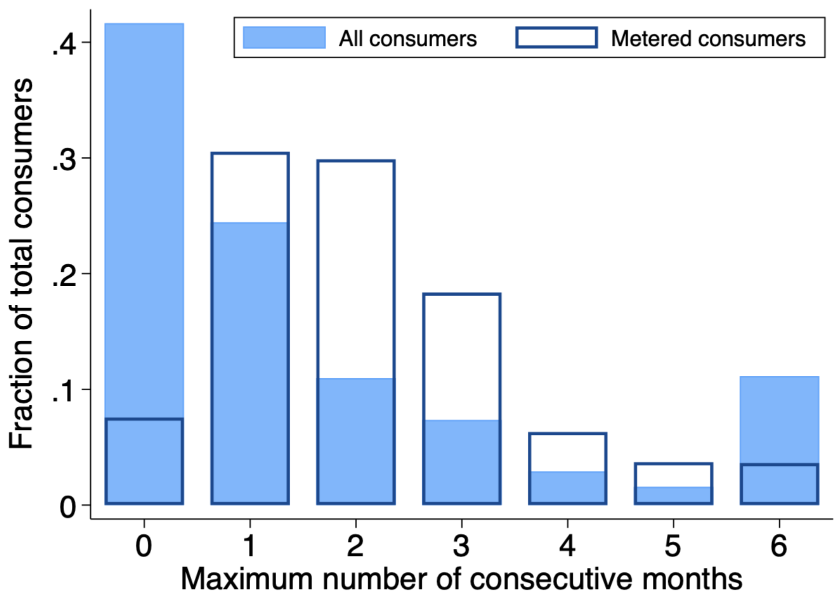
Table 1: Summary statistics

	Full population			Experimental Sample		
Covariate	Hoshangabad & Harda	Narsinghpur	All circles	Hoshangabad & Harda	Narsinghpur	All circles
Electricity consumption (kWh)	116.96 (118.94)	94.94 (70.11)	108.85 (104.22)	142.91 (113.66)	103.68 (56.78)	123.30 (91.95)
Arrears (Rs)	1,524.71 (4,459.23)	713.11 (3,840.83)	1,225.93 (4,260.09)	3,268.66 (3,632.73)	1,900.08 (2,119.04)	2,584.37 (3,051.48)
Net bill (Rs)	2,342.68 (6,236.42)	1,077.02 (2,358.50)	1,876.74 (5,195.70)	4,173.69 (4,659.33)	2,283.74 (2,316.19)	3,228.71 (3,798.63)
Payments (Rs)	363.64 (1,284.19)	321.04 (1,753.33)	347.86 (1,475.67)	582.37 (1,648.06)	122.79 (734.87)	352.58 (1,296.46)
Net bill payment percent	31.92 (45.81)	30.63 (44.44)	31.44 (45.30)	12.19 (29.39)	2.87 (15.29)	7.53 (23.89)
Percent of consumers who do not pay	0.66 (0.47)	0.65 (0.48)	0.66 (0.47)	0.83 (0.38)	0.96 (0.19)	0.90 (0.31)
Percent of consumers who partially pay	0.04 (0.20)	0.10 (0.30)	0.06 (0.24)	0.10 (0.30)	0.03 (0.16)	0.06 (0.24)
Percent of consumers who fully pay	0.30 (0.46)	0.25 (0.43)	0.28 (0.45)	0.07 (0.25)	0.01 (0.10)	0.04 (0.20)
Number of consumers	295,794	174,137	469,931	15,000	15,000	30,000
Number of DCs	35	22	57	35	22	57

Notes: The table shows means and standard deviations for pre-treatment outcomes among metered domestic households in August 2021. Standard deviations are shown in parentheses. Columns 2–4 show results for the full underlying population in Hoshangabad and Harda Circles (Column 2), Narsinghpur Circle (Column 3), and all circles combined (Column 4). Columns 5–7 show results for our experimental sample for Hoshangabad and Harda circles (Column 5), Narsinghpur Circle (Column 6), and all circles combined (Column 7).

First, non-payment is extremely common. Table 1 presents summary statistics for August 2021, prior to our experiment. The first three columns shows average consumption, arrears, payments, and bills for the population of metered domestic customers. The remaining columns show summary statistics for customers in our experimental sample, discussed below. On average, customers consume 123 kWh per month, and owe Rs. 3,228. However, the average monthly payment is only Rs. 352. Customers pay in full only 28 percent of the time, and they make no payments 66 percent of the time. Figure 1 shows the number of consecutive months the population of all domestic and metered domestic customers pay 100 percent of their bill from July through December 2021. Less than 20 percent of consumers pay 100 percent of their bill every month.

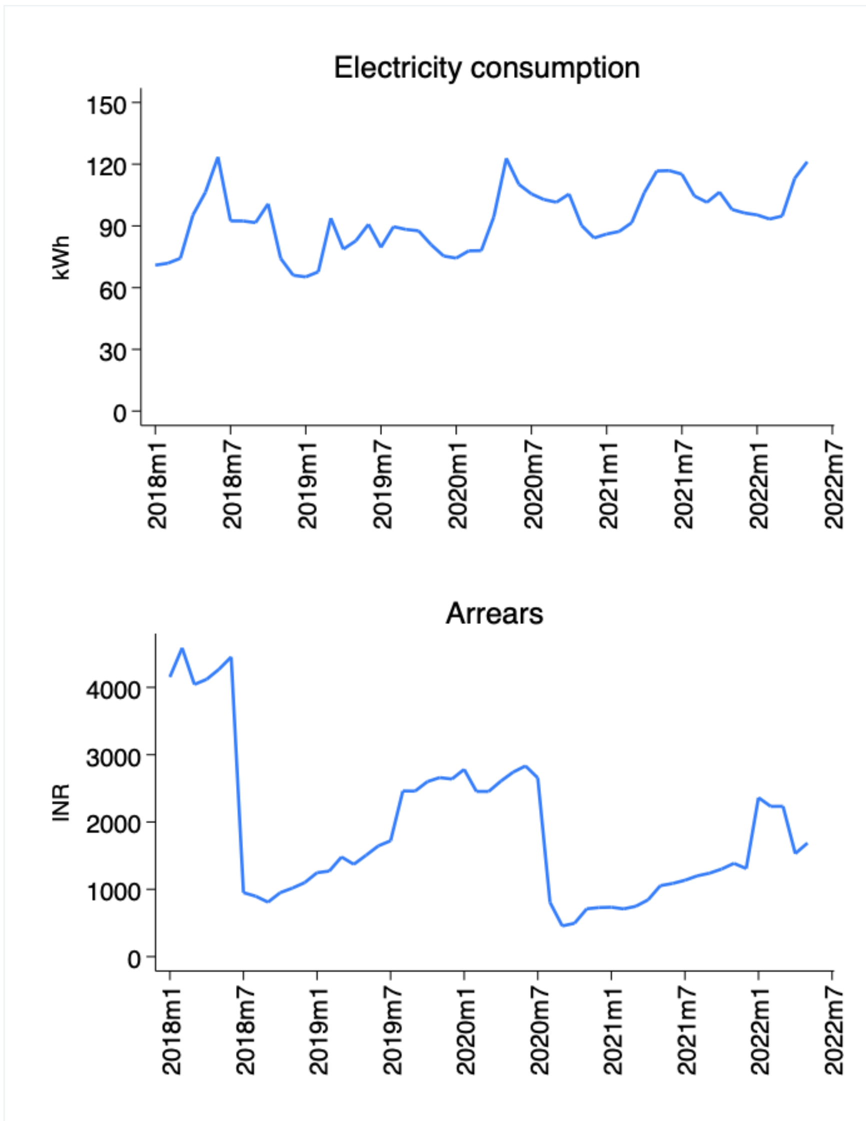
Figure 1: Consecutive bill payments, July through December 2021



Notes: The figure shows the distribution of the maximum number of consecutive months all domestic as well as metered consumers make full payments towards their monthly bill between July and December 2021. Customers with data in each month are included in the figure.

Second, periodic arrear waivers shift consumer debt to the state exchequer without changing the norm of non-payment. Figure 2 shows consumption and arrears from January 2018 through May 2022 for the population of domestic consumers in the Hoshangabad and Narsinghpur circles. Though consumption is relatively stable over time, arrears steadily increase, with two notable exceptions when the government introduced debt waiver schemes. Although removing accumulated household debt has often been described by the government as a way to make it easier for them to pay all dues in the future, the pattern of arrears shows little evidence this is true. Between July and December 2021, average arrears were Rs. 1262.

Figure 2: Electricity consumption and arrears, 2018 - 2022



Notes: The figure shows the time series of mean electricity consumption and arrears among domestic consumers from January 2018 through May 2022.

3 Experimental design

The experiment we describe here arose out of a partnership initiated in 2021 with two state-run utilities in Madhya Pradesh. The MPEZ and MPCZ together serve over 8.1 million households in the Eastern and Central regions of the state. As with other distribution utilities in the country, the state utilities of Madhya Pradesh have also struggled with recovering the costs of supplying power. In 2018-19, both utilities recovered less than 60 cents on every dollar of electricity supplied to consumers, even accounting for subsidy reimbursements provided to them by the state government.

Reducing these losses was and remains a priority of the central government in India, to the point where even the Covid recovery packages put together for state governments were conditioned on their taking steps designed to reduce losses.These incentives reward incremental improvements in revenue recovery, and gradual reductions in losses could also allow the state to supply more power holding constant total expenditure.

In this context we were asked by the utility to help evaluate the effectiveness of the different enforcement instruments available to them. Accordingly we designed an experiment to test the impact of different strategies on consumer payments. Given an institutional context characterized by severe budget and staff constraints, we consider both conventional enforcement methods that the utility had used before as well as lighter touch, lower cost methods. This paper focuses on early experiment outcomes but the end point of our partnership also envisages combining administrative data, household surveys, and experiment outcomes in order to define optimal targeting rules for the Madhya Pradesh utilities.

In what follows we describe different elements of the experiment in more detail.

3.1 Sample selection

The experiment sample consists of individual consumers in the Hoshangabad and Narsinghpur service regions (*circles*), served by MPCZ and MPEZ utilities respectively.[8]

These two circles were selected by the leadership of the holding company for the government utilities, who identified them because they represented areas with a significant non-payment problem, but possessed relatively good administrative data and were not in violence-affected areas.[9]

From the universe of utility consumers in these regions, we first excluded consumers on the so-called 'Below Poverty Line' tariff. Although households in this tariff class are not necessarily literally below the poverty line, they represent a class of consumers regarded as being economically vulnerable. As such the utility felt they should not be the target of new payment enforcement activities.

We also excluded (i) consumers whose meters were recorded as broken or missing, (ii) consumers with missing contact details in administrative records, and (iii) consumers who were inactive (zero consumption) in August 2021, the latest month for which we had data at the time of drawing the sample.

Finally, on the direction of our government partners, we filtered out households whose arrears as of August 2021 were less than Rs 1,200. In August 2021, this cut-off represented the 67th percentile of the arrears distribution. This ensured that enforcement actions - in particular disconnections - would not target customers whose arrears were (relatively) low. This restriction reflects the practical difficulties for the utility in targeting such consumers.

From the remaining consumer base, we drew a representative sample of 15,000 domestic (household) consumers in each circle. Thus our experiment excludes consumers billed on agricultural, industrial, commercial, or government tariffs. These households were assigned

8. In March 2021 — before the experiment was initiated — the circle of Hoshangabad was split into two distinct circles: Hoshangabad and Harda. The name Hoshangabad in this document refers to their union.

9. Madhya Pradesh suffers from violence linked to domestic insurgencies in certain areas which hampers governance on several dimensions and also would have made fieldwork and data collection dangerous.

to one of six groups as described below, following a stratified randomized design. Strata were defined using the household's Distribution Center (DC)[10], terciles of outstanding arrears as of August 2021, and whether consumers consumed above or below median levels in August 2021.

3.2 Experiment Arms

Households selected for the experiment were randomly assigned to one of the six groups as described below. These treatments were selected from a larger menu of options provided by the researchers to MPPMCL. This design therefore excludes options that the government felt were undesirable or infeasible. This included a proposal to increase late fees and to introduce a one-time debt waiver.

A. Pure control: 7,500 consumers were randomized into the pure control group, where utility employees are asked to engage in no communication with households about payments beyond the details automatically provided on the electricity bill. This experimental arm approximates a no enforcement setting.

B. Business-as-usual: 2,500 consumers were randomized into a the business-as-usual (BAU) group, where utility employees are given no special instructions, as distinct from the pure control.[11]

C. SMS message: 5,000 consumers were randomized to receive three rounds of SMS messages between January 2022 and July 2022. These messages were reminders of outstanding payments and drew attention to the risk of disconnection. The text of these messages reads (translated to English from Hindi)

10. A distribution center is the smallest administrative unit in the utility, and the local office level at which billing, collections, and disconnections are carried out. There are 57 DCs in our sample.

11. In this draft, we exclude the BAU arm from our analysis, because we are currently in the process of collecting data on what, if any, interactions they had with the utility.

"Dear Consumer, please pay your electricity bill on time. There is [X] percentage of your bill remaining on your electricity connection number [IVRS No]. If payment is pending, please pay immediately to avoid disconnection."

D. SMS social comparison message: 5,000 consumers were randomized to receive an SMS message comparing their payment behavior to that of their neighbors. These messages contained the same information as Treatment C but include a peer group comparison. This group consists of other households in the same strata as the message recipient. The text of these messages read:

"Dear Consumer, please pay your electricity bill on time. There is [X] percentage of your bill remaining on your electricity connection number [IVRS No]. Other similar consumers have [Y] percentage of their bill pending. If payment is pending, please pay immediately to avoid disconnection."

Note that both of these SMS reminders were a new addition to existing utility practice. They test a very low-cost and light touch approach to enforcement that does not involve physical disconnections but ex-ante was regarded as having the potential to be highly cost effective. These approaches are also inspired by a literature documenting the impact of peer comparisons on energy use behaviors (Allcott and Rogers (2014)) and the impact of simple reminders on tax payments (Neve et al. (2021)).

E. Mailed disconnection notice only: 5,000 consumers were mailed a formal notice by registered post. These letters were signed by the Managing Director of the electricity utility and warned the recipient that non-payment of electricity bills was a criminal offense, and that they had built up arrears that rendered them liable for disconnections if not paid within 15 days of receipt of the notice. Figure X contains an image of this letter whose text reads (translated to English from Hindi):

> You are being informed that electricity payment and other payment against your consumer ID: [IVRS No] amount of Rs. [X] are pending till month end [date].

> This has been informed to you earlier. Moreover, there is also a notice issued against the above mentioned consumer ID. You are being informed that if the pending electricity payment of Rs. [X] is not paid within 15 days of the issue of this notice, then under electricity Act, 2003, Section 56 [...] the electricity will be disconnected once the notified period comes to an end. Please keep in mind that minimum electricity charges will be applied till the entire pending amount is not paid in full. In the case that the electricity amount is not paid, you will be charged under Section 138, as a punishable offence.

Though the text of these notices was taken from existing utility templates, in the status-quo such letters were delivered in-person to consumers by local linesmen employed at distribution centres (DCs). The main innovation in this treatment arm involved the mode of delivery, which eliminated any utility intermediaries and removed the scope for communication between the local linesman and the consumer at the point of receipt. Furthermore local DC officials were not informed as to which consumers had been sent mailed these notices. Finally, sending notices by post resulting in a significant reduction in costs. A single letter sent by speed cost cost about 15 INR and involved no expenditure of utility staff time.

F. In-person disconnection notice only: 2,500 consumers were assigned to receive a disconnection notice identical to that in Treatment E, but delivered in person by a utility employee. This treatment arm aligns closely with a status quo utility activity.

G. In-person disconnection notice, subsequent disconnection: Treatment arms E and F involve warnings from the utility but no physical disconnections were to be carried out. Under Treatment Arm G, an additional 2,500 households were randomized to first receive an in-person disconnection notice (as in Treatment Arm F). Payments made in response to this notice were tracked over a 30-45 day period from receipt (the exact duration varied due to lags in how utilities updated collection records). After this period distribution centers were instructed by utility management to disconnect all consumers who had not paid off their arrears in full.

Note that at the time of distribution of the initial notices, this treatment arm is indistinguishable from Treatment F. Utility officials at the distribution centers were told that a disconnection list would be provided to them, but the identity of these consumers was not made known in advance. Therefore Treatment Arm G consists of two interactions - the first is identical to Treatment Arm F, and the second involves a physical visit by a utility linesmen instructed to disconnect those consumers whose arrears had not been cleared following the receipt of the notice.

This set of experimental arms enables us to measure the impacts of a series of enforcement actions ranging from very low-cost and light-touch (SMS messages) to high-cost, high-intensity enforcement (in-person notice with physical disconnections). Of this portfolio, the higher-cost and more punitive measures were the only options used in the status-quo.

3.3 Balance

In order to check whether randomization was successful, we compare the pure control group against the experimental treatment groups on outcome data collected between July and December 2021, prior to the start of the experiment. We measure consumption, monthly net bill, arrears, payment amount, and whether a household pays anything. Table 2 shows the results. Across all of these pre-treatment outcomes, the pure control group is statistically indistinguishable from each treatment group. In each treatment arm, consumption is close to the control mean of 139.9 (Hoshangabad) and 104.6 (Narsinghpur). Arrears are substantially higher than monthly payments in all groups, and the likelihood that a household pays is approximately 13 percent in Hoshangabad and 10 percent in Narsinghpur.

These results suggest that the control group and the treatment groups are comparable, and we can interpret any post-treatment differences in outcomes between the treatment groups and the control groups as the causal effect of the intervention.

Table 2: Experimental Balance

	Control	SMS	SMS-Social	Mail	In-person	Disconnect
Consumption (kWh)	122.2	121.8	121.6	122.5	121.0	121.6
		(0.70)	(0.59)	(0.81)	(0.38)	(0.68)
Net bill (INR)	3231.3	3308.6	3267.7	3269.9	3230.3	3273.2
		(0.27)	(0.59)	(0.61)	(0.99)	(0.62)
Arrears (INR)	2435.0	2481.8	2453.4	2440.1	2430.9	2460.2
		(0.39)	(0.73)	(0.93)	(0.95)	(0.71)
Payments (INR)	303.2	307.0	314.7	303.3	288.5	291.7
		(0.77)	(0.39)	(0.99)	(0.36)	(0.48)
Pay anything (=1)	0.12	0.12	0.12	0.12	0.11	0.11
		(0.98)	(0.86)	(0.94)	(0.64)	(0.45)
Observations	7500	5000	5000	5000	2500	2500

Notes: This table reports the balance of covariates in our study sample across various treatment arms and for each utility. The variables are consumer-level average values from Jul to Dec 2021 as reported in the administrative billing and payments data collected from the two utilities. Each column shows mean values of each variable for each treatment group with p-value from a test of the null that the difference between the corresponding treatment and control group is zero in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

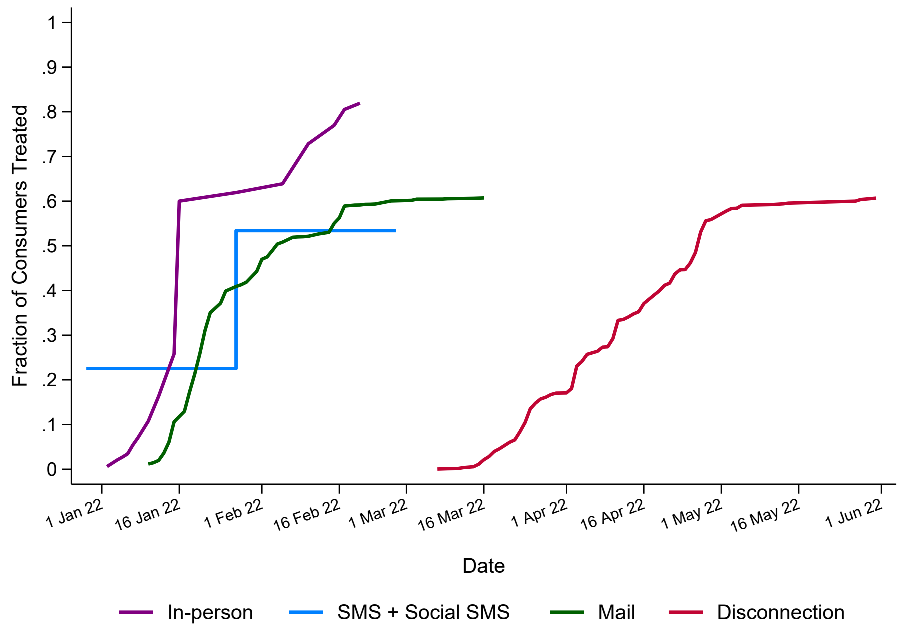
3.4 Compliance

Designing an experiment on paper — even where that paper is signed by senior government officials — does not automatically guarantee compliance. In our case we find strong evidence that assignment to a treatment makes it significantly more likely that a consumer was actually subjected to the specified intervention. However, the probability of being treated is below 100 percent across all groups. Figure 3 summarizes compliance rates in the experiment and we discuss some of the reasons for failing to treat households below.

In the case of SMS messages (Treatments C and D), 38 percent of treatment households did not receive messages for technical reasons (incorrect phone number, failed message delivery for reasons such as being switched off or outside service areas). A further 9 percent of messages were not sent because consumers had no pending arrears and utility staff determined they should not be contacted.

In the case of Treatment E — mailed notices — 21 percent of letters did not reach consumers because the postal service was unable to find the recipient and obtain a signature.

Figure 3: Compliance with treatment



Notes: This figure shows the time series of compliance with the experimental design. Each line presents compliance over time for a one type of treatment. Across all treatments, compliance grows substantially over time, but no treatment ends with 100 percent compliance. Disconnections take place later than the other treatments because households must first be visited (as in the in-person treatment), and then there is a waiting period before disconnections can occur.

In many cases this is likely to be because the address in utility records was incomplete but a delivery failure could also occur if the named recipient could not be found at the specified address. A further 18 percent of letters were not sent because the consumer had arrears below INR 1200 at the time of printing.

For Treatment F — hand delivered notices — about 18 percent of households randomized to receive these notices were recorded as not being given them because arrears were below INR 1200 at the time of notice printing. For the remainder, we are able to rely only on linesman records signed off by division engineers as to the delivery dates of notices with no independent verification.

For Treatment G — in-person notices followed by disconnections — about 17 percent of households were recorded as not being given notices because their arrears were below INR

1200. Only 61 percent of households were recorded as being visited for a disconnection. The reasons for non-compliance were idiosyncratic and varied by distribution center.[12]

A successful disconnection does not necessarily imply that the household stays without power. This is because disconnected households may reconnect themselves - either through the meter (which is not removed), or bypassing it entirely.

4 Analytical approach

We use three main specifications to estimate the effects of treatment on our outcomes of interest: an ANCOVA specification that recovers the average intent-to-treat (ITT) effect, an event study specification that recovers a dynamic intent-to-treat effect, and an instrumental variables specification that recovers a local average treatment effect (LATE).

Static ITT effects We estimate a simple ANCOVA specification to estimate ITT effects of each treatment on our outcomes of interest. Specifically, we estimate:

$$\bar{Y}_i^{Post} = \beta \cdot \text{Treatment}_i + \bar{Y}_i^{Pre} + \varepsilon_i \tag{1}$$

where $\bar{Y}_i^{Post}$ is the average value of the outcome of interest (e.g. arrears) for household i in the post-treatment period, Treatment_i is a treatment assignment indicator, $\bar{Y}_i^{Pre}$ is the average value of the outcome of interest during the pre-treatment period, and ε_i is an error term. We estimate this separately for each treatment, restricting the sample to households

12. Many local officials refused to carry out disconnections, citing a recently announced government arrear waiver as being evidence that stringent enforcement was not in line with government policy. A few officials were candid, stating that they had friends and relatives in the disconnection lists and therefore would find it difficult to follow them. Others cited time and staff constraints.

in the pure control group and households in a given treatment group only.[13] We estimate this jointly for Hoshangabad and Narsinghpur.

The coefficient of interest in (1), β, will recover the effect of being assigned to a particular intervention on our outcomes of interest. Because compliance with the experimental assignment is imperfect, as we document in Section 3.4, this recovers the ITT effect rather than the average treatment effect.

Dynamic ITT effects While these ANCOVA estimates are informative about average impacts, they do not provide information about the dynamic impacts of treatment. Therefore, we additionally trace out the time path of the effect of treatment using an event study specification:

$$Y_{it} = \sum_{s=-S}^{S} \beta_s \mathbf{1}[\text{Months to treat } = s]_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{2}$$

where $\mathbf{1}[\text{Months to treat } = s]_{it}$ is an indicator equal to one s months from the household specific date of treatment and zero otherwise. We omit month $s = -1$. In this ITT specification, we use the actual date of treatment to determine the for households that were actually treated. For households that were not treated but belong to one of the treatment groups, we assign them the earliest treatment date for their circle.[14] All $\mathbf{1}[\text{Months to treat } = s]_{it}$ indicators are set equal to 0 for control households. α_i and δ_t are individual and household fixed effects, respectively, and ε_{it} is an error term that we cluster at the household level. We estimate this regression separately for each treatment: the sample consists only of all households assigned to a particular treatment group and all households assigned to the control group. This specification provides us with a test of the identifying assumption: in the

13. Presently, we exclude Treatment Group B, the BAU group, from the estimation, as we are still collecting data on their interactions with the utility. Therefore, the experimental results compare the treatment groups to the pure control only.

14. For example, suppose legal letters are mailed to all households on February 01. Household i receives their letter on Feb 20. Household j receives their letter on March 10. Then event times are defined relative to Feb 20 for household i and March 10 for household j. Treatment households who never receive a letter are assigned the policy start date as before, February 01 in this example.

absence of selection and anticipation effects, we should also expect to see β_s close to zero for negative event time values (before treatment). Estimates of β_s for $s \geq 0$ recover the dynamics of how households respond to different interventions, both in the month of treatment and those that follow.

LATEs Our sample contains substantial non-compliance. In order to estimate LATE effects, we use a two-stage least squares approach based on our ANCOVA specification. In particular, we estimate the following system of equations:

$$\text{Treated}_i^{Post} = \eta \cdot \text{Treatment}_i + \bar{Y}_i^{Pre} + \varepsilon_i \tag{3}$$

$$\bar{Y}_i^{Post} = \gamma \cdot \widehat{\text{Treated}}_i + \bar{Y}_i^{Pre} + \varepsilon_i \tag{4}$$

where Treated_i is an indicator for treatment status. We instrument for treatment status with treatment assignment. All other variables are the same as in Equation (1) above. As above, we estimate this system of equations separately for each treatment type. γ is an estimate of the LATE.

5 Results

5.1 Static ITT effects

We begin by estimating Equation (1) for our main outcome variables: arrears, monthly electricity bill, electricity consumption, and payments. Table 3 presents the results.

We document several striking facts. First, the impacts of the SMS messages on arrears are statistically zero. Neither the standard reminder SMS nor the nudge SMS changes arrears, net bill, or consumption. These are relatively precisely-estimated null results: for the standard reminder SMS, we can reject effects on arrears larger than 3.2 percent of mean

Table 3: ITT estimates of treatments on key outcomes

	Consumption (kWh)	Monthly bill	Arrears	Payments
SMS	-1.226	-30.35*	-15.05	-8.118
	(0.864)	(13.97)	(45.83)	(7.904)
SMS Social	0.540	17.16	-31.69	2.934
	(0.912)	(16.71)	(46.38)	(8.149)
Mailed Legal Notice	-1.071	-15.12	-186.5***	15.89
	(0.986)	(14.97)	(42.04)	(8.406)
Linesman Legal Notice	0.0857	-14.95	-6.195	-1.307
	(1.234)	(19.42)	(54.93)	(9.642)
Linesman Disconnection	-2.889	-20.36	-183.5***	33.18**
	(1.635)	(17.10)	(52.85)	(12.50)
Observations	12500	12500	12500	12500
Dep var mean	124.9	749.8	3298.5	189.8

Notes: Regressions to estimate treatment effect on consumption, bills, arrears, and payments. The specification uses a cross-section of consumers in the experimental sample. The independent variables are the treatment dummy and pre-treatment consumer-level averages of the respective outcomes over three months prior to the receipt of treatment. The dependent variable is the post-treatment average defined in event-time for the whole period post the receipt of treatment for each consumer. For the control group, the date of receipt of treatment is randomly assigned based on the distribution of receipt dates in the treatment. Robust standard errors in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

arrears. The social comparison SMS also yields no change in arrears, and we can reject changes larger than 3.2 percent of the mean.

Next, mailed notices have a strong impact on arrears. The ITT effect of letters on arrears is INR -186.5, or 5.6 percent. This treatment effect is statistically significant at the 1 percent level. These results suggest that mailed notices – which only cost INR 15 to send – are a cost-effective way of reducing non-payment in the short run.

The results on the mailed notice stand in contrast to the effects of an in-person notice. Despite the actual notice being the same across the two treatment arms, in-person delivery of this notice has no statistically significant impacts on arrears, net bill, or electricity consumption in both circles. The ITT point estimates on arrears are substantially smaller than the effect of the mailed notice, with a point estimate of only INR -6.2, not distinguishable from zero. These results suggest that the method by which an enforcement action is taken is important for its effectiveness. In particular, receiving a formal letter delivered by registered post seems to significantly impact consumer behavior, while receiving the same letter from a local utility linesman – with whom customers regularly interact – has no impact. This is likely for one of two reasons: first, receiving a letter in the mail may affect households' expectations that they will be disconnected if they do not pay, while receiving the same notice from the linesman may mute the strength of this notice; second, linesmen may be engaging in side deals with households. In our endline survey, scheduled for November 2022, we plan to investigate these hypotheses.

Finally, we estimate the effect of electricity disconnections on consumer behavior. Disconnections, which are the most invasive and most costly treatment we evaluate, do impact consumer behavior. Perhaps most importantly, we see that being assigned to the disconnection group reduces arrears by INR 183.5 (5.5 percent of the mean). The disconnection treatment is a two-step process, where households first receive an in-person disconnection notice (i.e., are treated identically to the in person notice group), and then they are disconnected 1-2 months later if they have not paid. Given the null result in the in-person notice group, these reductions in arrears are directly attributable to the disconnections themselves. We also find evidence households increase their payments by INR 33.2, or 17 percent, in response to a disconnection. Interestingly, actual disconnections appear to have very similar effects to mailed notices, suggesting that there may be a more cost-effective way for utilities to reduce consumer debt than disconnecting households.

5.2 Dynamic ITT effects

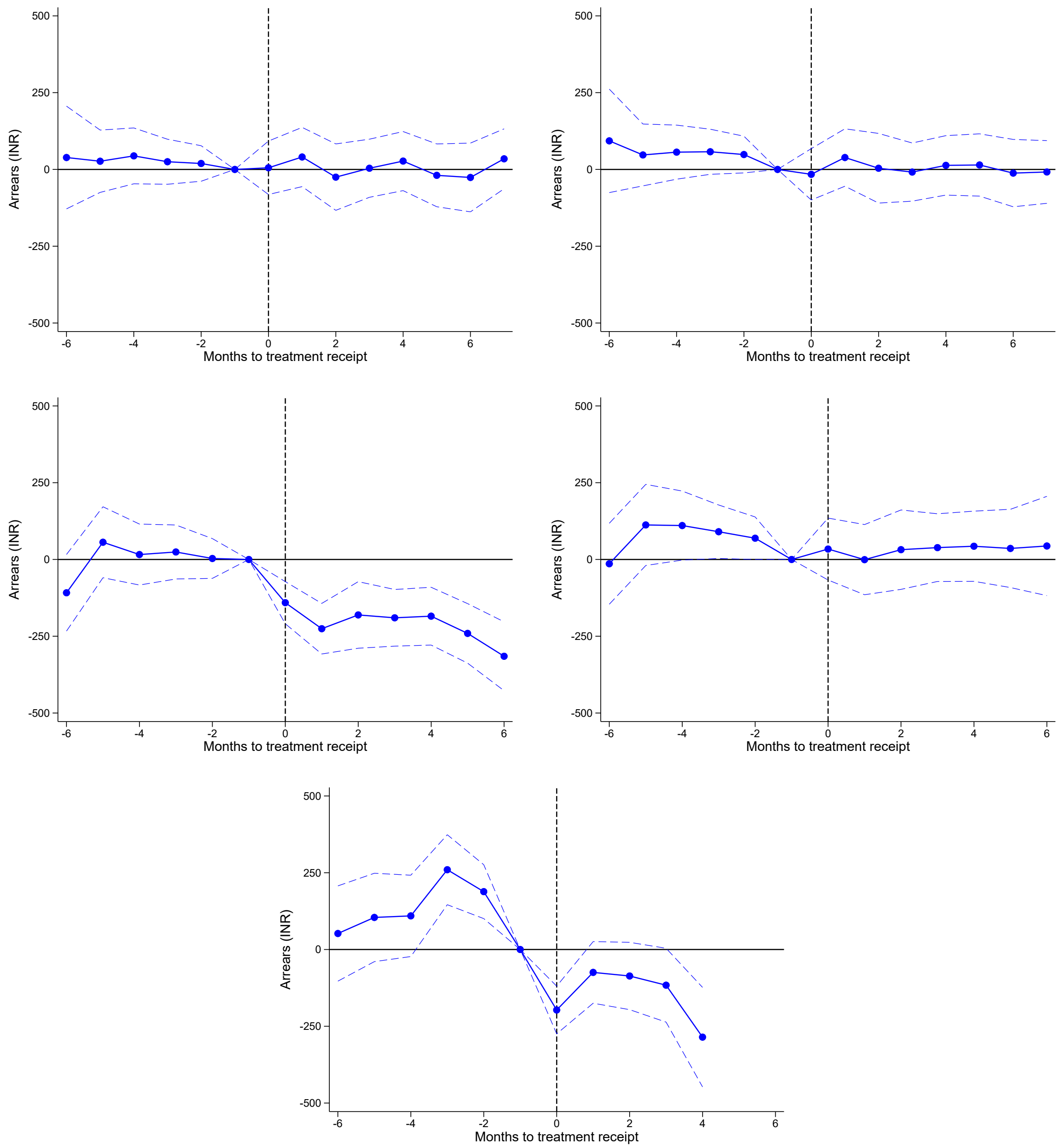
In addition to these main static ITT results, we use our event study specification (Equation (2)) to observe treatment dynamics. Figure 4 plots ITT impacts of each treatment type on arrears over time. Reassuringly, we find no difference between treatment and control households prior to treatment. Consistent with the static results in Table 3, we find no impact of either type of SMS message on arrears. We also find no impacts of in-person notices on arrears, but confirm the strong effects of mailed notices on arrears. The relatively flat pre-trends we observe prior to disconnection are consistent with the fact that in-person notices, which occur 1–2 months prior to disconnections, have no impact.

We find that disconnections have a strong impact on arrears: after treatment occurs, arrears fall. Because the disconnections occurred relatively recently, we only have a few months of post-disconnection data. We are extending this sample in ongoing data collection.

Figure 5 plots ITT effects of mailed notices and disconnections on arrears separately for Hoshangabad and Narsinghpur. As in Figure 4, we find that, prior to treatment, mail notice households and control households are similar in levels and trends. Both treatments cause meaningful declines in arrears that are sustained – or, if anything, increase in magnitude – over the four months after notices are delivered.[15] The fact that these estimates are similar in both discoms, despite essentially coming from independent experiments, speak to their robustness. Broadly, these event study estimates re-enforce the static ITT results,

15. In ongoing work, we are continuing to collect post-treatment data from both circles, which will allow us to trace out the longer-run dynamic effects of treatment.

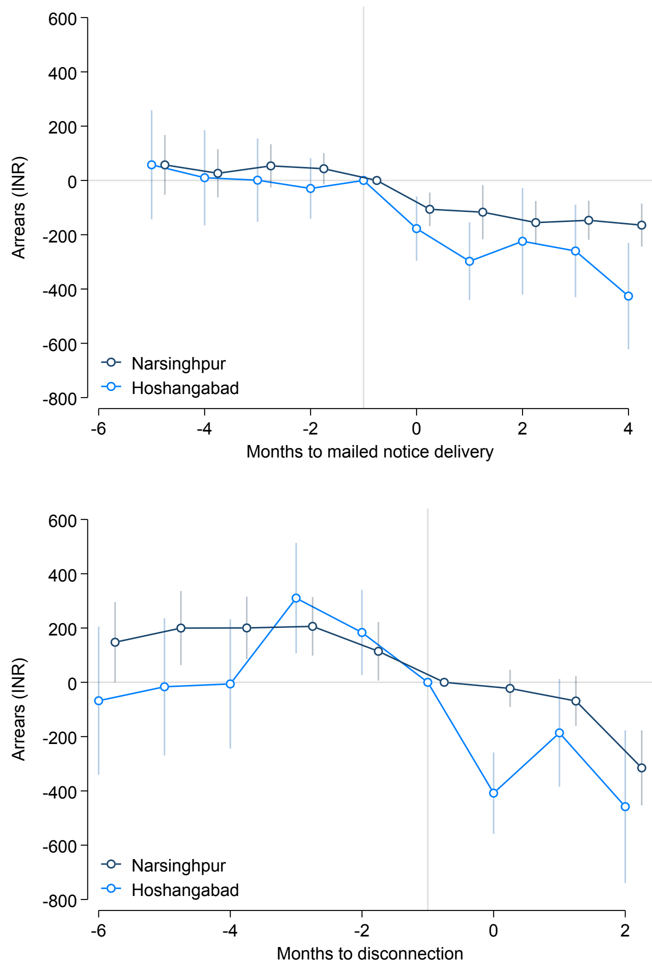
Figure 4: Event study estimates: Effects of treatments on arrears



Notes: This figure shows event study estimates of the impact of SMS messages, in-person notices, and disconnections on arrears, estimated using Equation (2). The top left panel plots effects for reminder SMSes; the top right panel plots effects for social comparison nudge SMSes; the center left panel plots effects for mailed notices; the center right panel plots effects for in-person notices; and the bottom panel plots effects for disconnections. All estimates are relative to the month before the treatment took place. 95 percent confidence intervals are shown in the dashed lines.

demonstrating that mailed notices and disconnections are both effective at reducing arrears, and suggest that these changes may last over the short-to-medium term.

Figure 5: Event study estimates: Split by circle



Notes: This figure shows event study estimates of the impact of mailed notices and disconnections on arrears, estimated using Equation (2). The top panel plots effects of mailed notices on arrears and the bottom panel plots effects of disconnections on arrears. The light blue line plots effects in Hoshangabad; the navy line plots results in Narsinghpur. All estimates are relative to the month before the treatment occurred. 95 percent confidence intervals are shown in the corresponding color for each circle.

5.3 LATEs

Finally, we present LATE estimates, which account for non-complaince. We present these results in Table 4. We again find no evidence that SMS reminders or SMS social comparisons impact arrears, and continue to find precise null results. We continue to find that the disconnection notice is effective when mailed, but not when delivered in person. The LATE effects of the mailed notice on arrears (INR -327.9, significant at the 1 percent level) are substantially larger than the ITT effects (INR -186.5), which aligns with non-compliance in mailed notice delivery. The mailed notice LATE is approximately 10 percent of the mean arrears. Again, given that mailing a letter costs INR 15, mailed notices appear to be quite cost effective. We now also find suggestive evidence that payments rise in response to mailed notices. We also find that disconnection visits are effective at reducing arrears, with a LATE of INR -306.1 (9.3 percent of the mean, significant at the 1 percent level), compared with an ITT of -183.5. We also find some evidence for an increase in payments in response to disconnections.

Table 4: LATE effects

	Consumption (kWh)	Monthly bill	Arrears	Payments
SMS	-1.032	-30.56	-43.34	-10.26
	(1.056)	(16.84)	(49.24)	(9.059)
SMS Social	0.898	21.54	-60.43	2.345
	(1.086)	(18.76)	(49.95)	(9.253)
Mailed Legal Notice	-2.108	-21.03	-327.9***	29.89*
	(1.681)	(25.55)	(71.10)	(13.92)
Linesman Legal Notice	0.226	-14.85	-12.10	1.890
	(1.603)	(24.52)	(68.36)	(12.84)
Linesman Disconnection	-3.843	-42.79	-306.1***	49.23*
	(2.541)	(30.48)	(84.78)	(21.48)
Observations	57494	57494	57494	57491
Dep var mean	127.1	721.8.5	3293.6	188.0

Notes: Regressions to estimate local average treatment effect (LATE) on consumption, bills, arrears, and payments. The specification uses a cross-section of consumers in the respective treatment group and control. The dependent variable is the post-treatment average defined in event-time for the whole period post the receipt of treatment for each consumer. For consumers in the treatment group who did not receive treatment, the post-treatment period is defined as the period post the earliest date of treatment in the group. For the control group, the date of receipt of treatment is randomly assigned based on the distribution of receipt dates in the treatment. The regressors are the *actual* treatment status, instrumented by treatment assignment, and pre-treatment consumer-level averages of the respective outcomes over three months prior to the receipt of treatment, again defined in event time. Standard errors in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6 Heterogeneity

We next test the extent to which our treatment effects are heterogeneous. This is useful for two reasons. First, we can learn about mechanisms that can inform future enforcement effort. Theory suggests that a household's response to enforcement activity should depend on its prior exposure to the utility. If a household has experienced prior enforcement, but this enforcement did not have bite, the household should respond less to future enforcement. On the other hand, if a household experienced prior enforcement that did have bite, the household should respond more to future enforcement. We test for this using households' historical exposure to enforcement. Households with "RC/DC" charges have had prior enforcement exposure. To estimate the extent to which this changes customers' responses, we run an interacted version of Equation (1), where we we interact the treatment indicator with a dummy for whether a household has had a prior enforcement experience. We have this historical enforcement data for Hoshangabad only, so we restrict the regression to this circle for this analysis. Table 5 presents the results. We find that our treatment effects are larger among households that have previously faced enforcement: the interaction term on mailed notices is INR -1702.9 (though this is noisy), and the interaction term on disconnections is INR -2402.5, statistically significant at the 5 percent level. These results suggest that prior enforcement with teeth can improve bill payment responses in future enforcement activities.

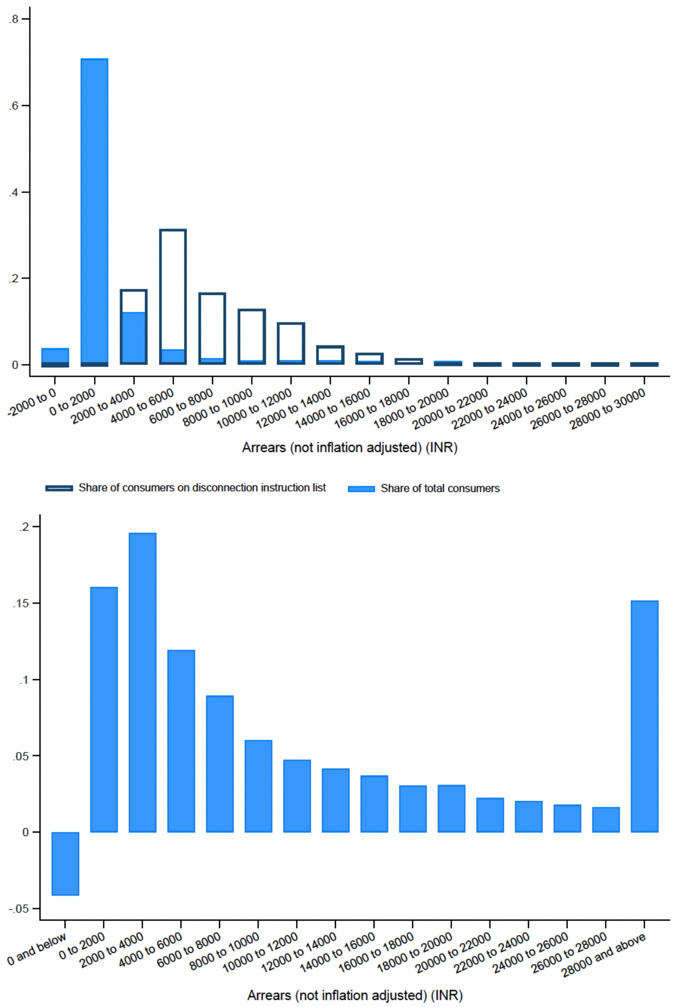
Table 5: ANCOVA with RCDC interaction term: Treatment effect on average monthly arrears - Hoshangabad

	SMS	SMS Soc	Mail	IP	DSC
Treatment dummy	-28.63	15.69	-199.9***	93.72	-229.6**
	(78.73)	(76.76)	(74.31)	(98.29)	(94.27)
RCDC charge	-1069.7	-1062.1	-864.8	-900.4	16.84
	(721.0)	(722.1)	(720.2)	(737.1)	(677.5)
Treatment dummy * RCDC charge	-711.7	350.5	-1702.9	-1961.9*	-2402.5**
	(808.6)	(1233.4)	(1068.9)	(1068.4)	(1061.0)
Pre-period arrears	1.104***	1.102***	1.079***	1.056***	0.820***
	(0.0382)	(0.0406)	(0.0354)	(0.0381)	(0.0254)
Constant	738.3***	745.3***	671.8***	800.5***	458.1***
	(107.3)	(114.3)	(106.9)	(106.6)	(94.25)
Observations	6250	6249	6249	5000	4998
Dep var mean	4228.0	4206.1	4138.5	4210.1	4002.9

Notes: Regressions to estimate treatment effect on arrears. The specification uses a cross-section of consumers in the experimental sample. The independent variables are the interaction of the treatment dummy and the RCDC dummy (defined as having received at least one RCDC charge in 2021), and pre-treatment consumer-level averages of the respective outcomes over three months prior to the receipt of treatment. The dependent variable is post-treatment average arrears defined in event-time for the whole period post the receipt of treatment for each consumer. For the control group, the date of receipt of treatment is randomly assigned based on the distribution of receipt dates in the treatment. Robust standard errors in brackets. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Second, while mailed notices and disconnections are likely cost-effective on average, the utility may be able to improve its approach further by targeting customers with the strongest responsiveness. In the status quo, the utilities are targeting enforcement against households with the largest arrears, as shown in Figure 7.

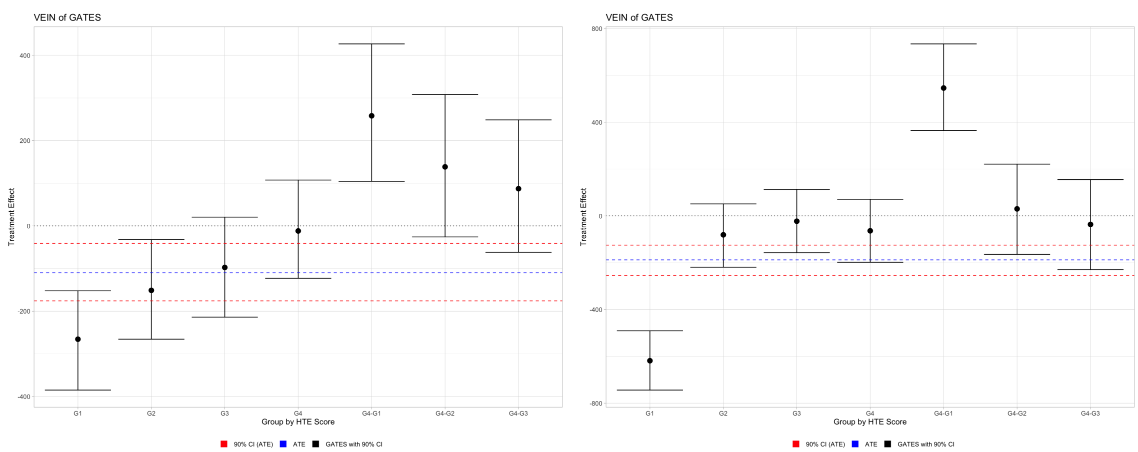
Figure 6: Targeting in the status quo



Notes: This figure shows targeting of pre-existing enforcement effort in Hoshangabad, where we have data. The top panel shows the distribution of all customers by arrear bucket (solid blue bars), and the distribution of customers who have been put on a list to be disconnected by arrear bucket (hollow navy bars). Disconnection instructions are skewed towards high-arrear customers. However, the bottom panel shows the overall distribution of arrears, highlighting that a significant share of all arrears comes from customers with relatively low per-customer arrear levels.

We therefore aim to predict treatment effects using characteristics that are available to the utilities. To do this, we use the Chernozhukov et al. (2018) generic machine learning approach. This method uses machine learning tools to split the sample based on predicted effect sizes, allowing correct inference on a ML-augmented RCT estimator. We allow the algorithm to flexibly use distribution centre fixed effects, electricity consumption prior to the experiment, and arrears prior to the experiment as predictors. Figure **??** presents the results. The first four columns show the treatment effects for each quartile of predicted treatment effects. The left panel presents results for mailed notices, and the right panel presents results for disconnections. We find that there is likely room for the utility to improve by employing targeting, particularly in disconnection treatments, where the first quartile has substantially larger treatment effects than quartiles two, three, and four, where the effects are indistinguishable from zero.

Figure 7: Machine-learning-predicted treatment effects



Notes: This figure shows the results of the Chernozhukov et al. (2018) GATES prediction exercise. The left panel shows heterogeneous treatment effects for mailed notices, while the right panel shows effects for disconnections.

7 Conclusion

Non-payment of utility bills presents a significant challenge for governments in developing countries, with state electricity sector debts exceeding the entire budget of other key ministries. Despite utility efforts to reduce these debts, improving payments has proven difficult.

In this paper, we document preliminary results from a randomized controlled trial on enforcement involving 30,000 households in two utilities in Madhya Pradesh, India.

We have three key findings. First, we document that it is possible to reduce arrears in the short run using tools that are readily available to the utility. We demonstrate that both official notices mailed to households and disconnections themselves have a substantial effect on arrears. We find these treatment effects in both utilities. However, we find no evidence that simple reminder notices and SMS messages, which have been shown to change behavior in other contexts, reduce arrears whatsoever. This suggests that there are limits to simple behavioral nudges in an important setting where state capacity is limited and these interventions may have *ex ante* been very appealing.

Second, we show that the mode of delivery may be an important determinant of the effectiveness of enforcement actions. We delivered an official letter warning households that if they do not pay their outstanding bills, they will be disconnected, in two different ways: through registered post, and in-person via a utility linesman. We find that the mailed notices generate significant impacts, while the in-person notices have no effects. This may arise due to familiarity with the linesman leading him not to represent a credible threat to the household, or may reflect side deals between the linesman and the household. Distinguishing between these two mechanisms is a subject of our ongoing work.

Finally, we demonstrate that our treatment effects display heterogeneity. We find that this heterogeneity is predictable using data available to the utility, which may be able to substantially increase cost-effectiveness.

In ongoing work, we are extending this analysis in several ways. W will continue to collect administrative data, which will allow us to estimate changes in treatment effects over time. While the mailed notice and disconnections are effective in the short run, it is important to understand whether these effects remain stable or deteriorate over time. We are also in the process of collecting additional data on utility interactions with consumers, which will allow us to estimate treatment-on-treated impacts.

In addition, we are conducting two novel surveys that will shed additional light on our estimates. We are surveying utility distribution centre officials to better understand the costs of various enforcement actions to the utility. We are also conducting an endline survey of households. This will enable us to understand customer expectations and collect data on norms around electricity payment. Moreover, this survey will allow us to measure the impacts of utility enforcement on non-utility behaviors, such as consumption, and loans.

Lastly, using a combination of survey data and administrative data, we will extend the heterogeneous treatment effects found here to also include information about local-level utility enforcement and household characteristics that are absent in the utility administrative data. With both standard econometric and machine learning tools, we can determine optimal targeting of enforcement activity from both the utility and the household perspective.

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