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The long-run value of electricity reliability in India[☆]

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ABSTRACT

This paper evaluates residential consumers' electricity consumption and appliance investment responses to power outages from 2015 to 2019 in Delhi, India. Our empirical strategy takes advantage of features of the electricity distribution network in the service territory of one of Delhi's regulated distribution utilities that exposes similar customers to plausibly exogenous annual variation in electricity reliability. Using original household survey data and four years of billing and power outage records for more than one million customers, we estimate that an additional hour per month of power outages reduced electricity consumption by 4.8 percent. These estimates suggest that households are willing to pay USD 1.50 per kWh of lost consumption, which is more than 25 times the average price they pay for grid electricity.

In 2018, the Government of India announced that it had completed electrification of nearly every one of the more than 640,000 villages in the country. About six months later, the government followed with the announcement that more than 99 percent of its 1.34 billion people were connected to the electricity grid (Government of India, 2018). Just 15 years prior, India's electrification rate was less than 70 percent, suggesting that on average about 44 million people per year gained access to the electricity grid during this period.[1] Meanwhile, the country's fleet of power plants more than tripled its generation capacity during the same period, largely erasing persistent deficits in peak capacity that caused widespread blackouts in decades past (Central Electricity Authority, 2017).

In spite of this rapid expansion of electricity infrastructure, prolonged power outages remain a near-daily experience for most of India's electricity consumers. A recent survey of six of India's most populous northern states found that rural households faced 11 h of electricity outages on average every day (Aklin et al., 2016). Outages remain common across India for four principal reasons. First, many of India's state-owned electricity distribution utilities engage in short-term non-price rationing of electricity through load shedding, or rolling blackouts. Under load shedding, distribution utilities balance demand and supply by curtailing the availability of power to retail consumers instead of purchasing sufficient wholesale electricity to serve these consumers (Jha et al., 2022). Second, rapid growth of electricity consumption has outpaced the capacity of electricity grid in many regions of India (Pargal and Banerjee, 2014). Per capita electricity consumption in India has been growing at a rate of 3.5 to more than 8.5 percent per year since the early 2000s.[2] Each element of the high voltage transmission grids and low voltage distribution grids have capacity limits that govern the maximum amount of power that can flow over them in any instant. Capacity shortfalls at various points either result

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[1] World Bank (2019): Access to electricity (% of population): https://data.worldbank.org/indicator/eg.elc.accs.zs.

[2] World Bank (2019): Electric power consumption (kWh per capita): https://data.worldbank.org/indicator/EG.USE.ELEC.KH.PC.

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in equipment failures due to overloading or necessitate load shedding to prevent overloading. Third, maintenance of existing grid infrastructure has also lagged across much of the country as state-owned distribution utilities have fallen deep into debt (Power Finance Corporation Ltd., 2016). Deferred maintenance contributes to higher rates of equipment failures throughout the network, often resulting in outages. Finally, outages are also caused by idiosyncratic external factors, in particular severe weather. Between June and September, India's monsoon rains and wind are responsible for frequent losses of power to large swaths of the country. During the monsoon season, distribution utilities often face a long backlog of down infrastructure caused by flooding, lightning strikes, falling trees, and high winds.

Frequent load shedding, insufficient investment in the distribution grid, deferred maintenance, and even slow responses to weather-related idiosyncratic outages reflect the incentives of the distribution utility to provide high quality service. For decades many of India's state electricity operators have struggled to rise out of severe infrastructure quality and subsidy traps of the kind analyzed in McRae (2015). Retail tariffs are highly redistributive across customer classes, making large segments of the customer base loss-making on average. In the case of agriculture, consumption is often unmetered, which prevents utilities from charging a marginal price for electricity and customers from facing an incentive to conserve usage. In response, utilities resort to a variety of explicit and implicit forms of non-price rationing of electricity to mitigate their losses, which in turn undermines the value of the service to the public as well as the rationale to raise prices, meter connections and enforce bill payments. Widespread theft, non-payment of bills and unmetered connections are part of this self-reinforcing cycle (Burgess et al., 2020). As a consequence, poorly performing state-owned distribution companies have come to depend on regular cycles of central government bailouts and have resisted reforms.

An important contributor to the dysfunction is that the design of the electricity market in this setting is not informed by how much consumers are actually willing to pay to avoid power outages, a concept known as the value of lost load (VoLL). In contrast, the VoLL has been deeply influential in the design of electricity markets in North America and Europe (Hogan, 2013). It is an essential policy parameter for decision-making on reliability-enhancing investments, such as investments in transmission and distribution, through cost–benefit analysis. The VoLL can inform the design of efficient retail pricing mechanisms such as dynamic pricing and demand response programs that offer consumers incentives to turn off low-value end uses during periods of shortage and help mitigate the supply–demand imbalances that often cause outages (Gorman, 2022).[3] The literature on VoLL has focused largely on using a variety of stated preference and proxy methods to estimate the costs of infrequent, unexpected power outages in developed country settings in which outages are rare (Woo and Pupp, 1992; van der Welle and van der Zwaan, 2007). In many developing countries, power outages are frequent and at least partially predictable, rendering many of the assumptions used to estimate VoLL in developed country settings untenable. While recent studies in development economics have sought to use program evaluation methods to evaluate the benefits of electricity reliability, none of them estimate the VoLL directly.

This paper provides evidence on the long-run value of electricity reliability to residential electricity consumers in Delhi, India. Through a confidentiality agreement signed with one of Delhi's electricity distribution utilities, we gained access to records on about 79 million individual electricity bills and hundreds of thousands of power outages for the company's more than one million residential electricity customers from 2015 to 2019. We then conducted a household survey of more than 3,000 of these customers and linked the survey responses to each respondent's electricity billing and outage history. Together, these data enable us to construct a uniquely detailed record of household-level electricity reliability and energy consumption over an approximately four year period, along with a rich set of demographic characteristics and appliance investment and ownership information for a subset of these customers.

Our empirical strategy takes advantage of features of the electricity distribution network in the service territory of the utility that generate differential patterns of power outages for similar customers from year-to-year. The utility we study monitors and manages both planned and unplanned power outages at the distribution feeder level. Distribution feeders are power lines that serve geographic clusters of between a few and a few thousand retail customers. In addition to sharing the power line itself, customers on the same feeder also share other pieces of distribution infrastructure, including transformers. In Delhi, and throughout much of India, commercial and industrial customers have historically been charged relatively higher electricity prices to account for the loss of revenue from subsidizing residential and agricultural customers who are charged tariffs that often cover less than 50% of the cost of supply. A higher level of cross-subsidization, which we define as the retail tariff gap between commercial and industrial (C&I) and residential customers, incentivizes the utility to prioritize feeders with a larger share of commercial and industrial customers as these customers drive up the average revenue that the utility can expect to earn by supplying an additional unit of electricity to these feeders. The tariff gap changes roughly once each year as the Delhi Electricity Regulatory Commission (DERC) revises retail tariffs for each customer category. Retail tariffs were revised three times during our sample period.

We employ a Bartik-style instrumental variable approach to study the effects of changes in the level of outages on electricity consumption of residential customers. Our main specification uses the proportion of C&I customers on each feeder interacted with aggregate changes in the tariff gap between C&I and residential customers as an instrument for the duration of outages affecting customers in a year. We estimate that an additional hour per month of power outages reduced electricity consumption by about 4.8 percent. Using our estimates of the price elasticity of demand from the same setting, these reduced-form estimates enable us to produce among the first revealed preference estimates of the long-run value of electricity reliability that exist to our knowledge.

This paper aims to contribute to growing literatures on the effects of energy access on development outcomes, the value of electricity reliability in developing countries, and the governance of state-owned public service distribution companies. A large literature

[3] Dynamic pricing schemes such as real-time or critical peak pricing increase the price of electricity during periods of shortage. Demand response programs pay consumers to give an external party such as their utility control to reduce their low-value end-use devices.

in development economics focuses on the relationship between energy access, energy consumption, and a variety of development outcomes. Much of this literature attempts to understand the extent to which energy access enables or is enabled by rising incomes. The evidence produced by several well-identified causal studies in South Africa, Brazil, Ethiopia, India, the Philippines and Kenya is mixed. Using an instrumental variable strategy to identify the economic impacts of electrification, Dinkelman (2011) finds that female employment increased as a result of a rural electrification program in South Africa. The paper uses the land gradient, a geographical feature that is positively correlated with the cost of installing transmission infrastructure, to instrument for treatment status under the program. Lipscomb et al. (2013) instrument for the placement and timing of hydroelectric dams in Brazil with predictions from an engineering model, and find long-run increases in housing values and other development outcomes. Barron and Torero (2017) show positive spillover effects of grid-connected households to non-electrified households in Ethiopia. Using measures of transmission cable density as instruments for the electrification status of households, Chakravorty et al. (2014) finds that high-quality grid connections increase non-agricultural incomes in India. Taking a similar approach, Chakravorty et al. (2016) shows that rural electrification has large positive impacts on household incomes and expenditures in the Philippines. Together, these studies suggest that electrification may be an important driver of increasing productivity and reducing poverty across heterogeneous settings. Other studies find long-term positive impacts on manufacturing, household consumption, household air quality, and agricultural production (Rud, 2012; van de Walle et al., 2013; Kitchens and Fishback, 2015).

On the other hand, Burlig and Preonas (2018) and Lee et al. (2020) find that the benefits of rural electrification in India and Kenya, respectively, may be small relative to the costs. Burlig and Preonas (2018) use a regression discontinuity design to study the effect of a rural electrification program in India on community-level labor market outcomes and household asset stocks. They show evidence that India's massive Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) rural electrification program, which began in 2005 delivered at most very modest improvements in outcomes like asset stocks, employment, income, and school enrollment. Lee et al. (2020) generate exogenous variation in the price of a grid connection and scale of the local construction project by providing randomly selected clusters of households with an opportunity to connect to the grid at subsidized prices. As a result, they can estimate both the demand curve for grid connections among households as well as the average and marginal cost curves associated with household grid connection projects of varying sizes. Comparing the demand and cost curves to assess the welfare implications of mass rural electrification, they find that consumer surplus from grid connections amounts to less than one quarter of total connection costs.

Our analysis addresses two issues raised by the mixed evidence on the benefits of electricity access presented in these studies. First, one potential explanation for the range of benefit estimates seen across these papers is that the quality of electricity service for the grid-connected population may vary substantially. As Aklin et al. (2016)'s survey evidence has shown, recently-electrified rural populations in India often cannot expect more than 12 h of electricity service each day. Poor service quality may undermine the ability of these populations to substitute electricity for other energy services, thus undermining the potential productivity gains from an electricity connection. A second potential explanation for the differences in the findings across these settings is the time scale over which these studies analyze outcomes. Benefiting from electrification involves a joint investment problem: households cannot make use of an electricity connection without appliances, and they are unlikely to own many appliances without an electricity connection. Although the fixed cost of connections are often subsidized, maintaining an account generally involves a fixed monthly payment. As a result, we might expect that the benefits of an electricity connection accrue relatively slowly over time while households accumulate appliance stocks. Our analysis addresses both of these issues by evaluating how residential appliance stocks respond through time to service quality.

A smaller literature exists on the costs of poor electricity reliability in developing countries. Allcott et al. (2016) estimate the effect of power shortages on industrial productivity in India by instrumenting with short-run supply shifts in hydroelectric availability, and show that shortages disproportionately affect smaller plants with less backup generation capacity given the large economies of scale in generator costs. This paper does not consider how investments in appliances and backups adapt in response to outages, which is especially important in settings where outage frequencies are high. McRae (2015) estimates a structural model of household electricity demand in Colombia and predicts the change in consumption and profits from upgrading low-quality electricity connections, but assumes outages are exogenous. Existing subsidies, which provide greater transfers to areas with unreliable supply, deter investment to upgrade infrastructure, which could lead to worse reliability. The quasi-experimental approach we utilize in this paper accounts for the potential endogeneity of outages.

We develop market-based estimates of VoLL that are directly comparable to those used in many electricity market regulatory regimes.[4] The approach we use combines our reduced form estimates of the long-run effects of outages on consumption as well as our estimates of long-run price elasticities of demand for residential consumers from the same setting (Khanna and Rowe, 2022).

[4] There are a few market-based approaches for estimating VoLL (Woo and Pupp, 1992). The consumer surplus approach estimates outage costs by equating them to compensating variation or the area under the compensated demand curve for electricity (Sanghvi, 1982). Willingness to pay (WTP) for each unit of electricity depends on the degree to which the consumption of each unit can be deferred, or substituted, to another hour. If a large part of electricity consumption in the morning hours is considered essential, or costly to defer, then this information is revealed by the demand function being more inelastic in those hours. Consequently, the consumer surplus loss, which is equivalent to the household's WTP to avoid a total outage, is larger in those hours. A key drawback of this approach is that WTP for planned electricity consumption may not be equivalent to WTP to avoid unplanned interruptions. Another market-based approach uses data that utilities collect from offering interruptible or curtailable service rate options to large commercial and industrial customers. Assuming consumers maximize their expected net benefit of electricity consumption, the data can be used to infer the compensation required for each customer such that they would be indifferent between the rate/reliability choice they made and the alternatives. These compensating differentials measure WTP for different reliability levels. A third approach uses the amount of installed back-up power as a revealed value of outage costs.

To compute the marginal willingness to pay to avoid an additional hour of outage, we divide the elasticity of consumption with respect to an hour of outage by the price elasticity of demand.

Finally, this paper also addresses the governance of state-owned companies. Across many countries and many policy settings, policymakers have struggled to increase the quality of public services. Burgess et al. (2020) argue that treating electricity as a right, as manifested by subsidies, widespread theft and non-payment, effectively severs the link between payment and supply, where those evading payment receive the same quality of supply as those who pay in full. The resulting low-quality, low-payment equilibrium is what differentiates electricity markets in developed and developing countries. While regulatory mandates often require utilities in developed countries to incur the cost of delivering 24x7 power supply, below-cost regulated retail tariffs for large swaths of the customer base in developing countries make reliability a choice variable for these utilities. Our analysis is intended to provide direct evidence on the question: could India's electricity distribution utilities improve welfare by investing in higher levels of reliability and recovering the costs of these investments through higher retail electricity prices?

The paper is organized as follows. Section 1 describes the survey we conducted and the electricity billing and network data we use in the analysis and provides an overview of key summary statistics. Section 2 details the empirical strategy we use to estimate the causal effect of power outages on electricity consumption. Section 3 presents the results and discusses the implications of our findings, particularly in the context of recent policies that were introduced to improve electricity reliability in Delhi. Section 4 concludes with a discussion of the areas where additional research is needed.

1. Data and summary statistics

The analysis draws on data from two principal sources. First, we obtained billing and power outage records for 2014 to 2019 for the universe of customers served by one of Delhi's three private distribution utility companies through a confidentiality agreement. Second, we augmented these data by conducting a household survey of residential customers served by the utility and matching the survey responses to customers' billing and power outage histories using their unique customer number. The resulting dataset enables us to observe four full years of billing records and reliability statistics in addition to detailed demographics and appliance information for the sample of households surveyed. This section describes each of the two data sources in turn and provides summary statistics for the sample of customers used in estimation.

1.1. Customer bills and outage data

Customers receive electricity bills from the distribution company on approximately monthly cycles. In addition to the total amount payable in rupees (INR), the customer billing data includes total consumption in kilowatt hours (kWh), detailed breakdowns of individual fixed and volumetric charges, subsidies and rebates received, past unpaid balances, and the posting and due date of the bill.

Using data on individual power outages, we construct a measure of electricity reliability on the distribution feeder line serving each customer during the billing period of each bill. Outages are observed at the distribution feeder level. A distribution feeder is a power line running out of a substation to the transformer that steps it down to its final voltage and finally to customers. The utility's network comprises about 1100 feeders during the sample period, each of which serves approximately 1700 customers on average. Distribution feeders are the lowest level of the electricity network at which the utility can conduct load shedding, that is, rolling blackouts, centrally. Outages that occur due to equipment failures or weather events, however, may affect a subset of the feeder. While we observe the number of customers affected by each outage, we do not directly observe which individual customers are affected by each outage. Instead, we use a cross-sectional dataset provided by the utility that links each individual customer's meter to the feeder line it is supplied power by, which allows us to construct a detailed picture of electricity reliability at the meter level. We use as our measure of electricity reliability the System Average Interruption Duration Index (SAIDI), which is the average duration of outages per customer per year.[5]

1.2. Survey of residential electricity customers

We surveyed 3,181 households in Delhi served by the electric utility we study between July and September 2019. The sampling followed a three-step procedure. First, we drew a random sample of 48 electoral wards, each of which has a population of approximately 60,000. The sample of electoral wards was stratified on the tercile of Scheduled Caste population, a proxy measure for poverty. Second, we divided wards into 300 meter by 300 meter cells, removing unpopulated areas using the European Space Agency Climate Change Initiative's Land Classification data product,[6] and randomly drew a sequence of cells from each ward. Finally, survey teams conducted random-walk door knocking in the sampled cells, beginning each day in a new sampled cell until they completed 67 surveys in each ward. Households were asked to provide their unique customer number from their electricity

[5] The formula for calculating SAIDI is expressed below. i indexes outage events and t the time period. In 2016, the annual average SAIDI in the U.S. was 4.17 h, 2.3 of which were attributable to snowstorms, hurricanes, floods, fires, and heatwaves (US EIA, 2018)

$$SAIDI_t = \frac{\sum_i (\text{Duration}_i \times \text{Customers Affected}_i)}{\text{Number of Customers}}.$$

[6] ESA-CCI LC data are available online: https://www.esa-landcover-cci.org/?q=node/164.

Table 1
Summary statistics.

	Mean (1)	Std. Dev. (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)
Panel A. Customer-Year							
Contracted load at beginning of year (KW)	2.28	1.56	1	1	2	3	6
Billed kWh per bill day	7.67	5.34	1.15	3.92	6.49	10.1	18.6
Mean tariff in year (INR/kWh)	4.56	10.9	2.52	2.97	3.38	4.91	7.07
Total subsidy received in year (INR)	3282.9	1707.5	450	2112	3195.6	4386.2	6260.0
Change in contracted load (KW)	−0.18	0.75	−2	0	0	0	1
Mean arrears on bills in year (INR)	329.5	1521.9	0.84	1.96	61.3	284.4	1497.1
Number of bills in year	9.89	1.74	7	9	10	11	12
Mean outage hours per customer per month	2.64	4.01	0.032	0.28	0.88	3.27	11.0
Observations	3,350,052						
Panel B. Feeder-Year							
Mean residential contracted load on feeder	2.59	1.15	1.09	1.66	2.40	3.33	4.77
Billed kWh per bill Day	37.3	115.6	5.05	7.64	11.5	19.6	166.4
Mean tariff in year on feeder (INR/kWh)	7.46	1.95	4.69	6.06	7.19	8.90	10.6
Commercial and industrial customer share	0.23	0.25	0.021	0.078	0.13	0.25	0.93
Residential customer share	0.75	0.26	0.030	0.74	0.85	0.91	0.97
Observations	2,903						

The table reports summary statistics at the customer-fiscal year level (Panel A) and the feeder-fiscal year level (Panel B).

bill as part of the survey, enabling us to link their survey responses to their history of electricity bills. We successfully linked 3,034 of the 3,181 survey respondents to their household's electricity bill.

The survey comprised four sections. The first section collected demographic information, including household income, family composition, and basic dwelling characteristics. The second section covered back-up power – battery inverter kits and diesel generator sets – investment, ownership, costs, and usage. The third section collected detailed information on electrical appliance investment, ownership, and usage. The final section asked a series of qualitative questions about households' perceptions of and responses to power outages.

1.3. Summary statistics

Our main estimation sample is comprised of about 2.8 million customer-year observations for residential customers served by the utility for its 2015 to 2018 financial years, which run from April to the following March. Table 1 provides summary statistics at the customer-year level in Panel A and at the feeder-year level in Panel B. The mean daily consumption in the sample is 7.67 kWh per account, or about 230 kWh per month, more than 3 times the national average and less than 20 percent of US monthly consumption in 2017.[7] We limit our attention to customers with contracted loads of ten kW or less. Contracted load refers to the total allowable wattage of connected appliances or the load, in kW or kVA, that the utility has agreed to supply the customer. The utility revises the contracted load each year by taking the highest average of the customer's maximum demand readings for any four consecutive months in the previous financial year (i.e. April 1 - March 31) and rounding to the lower integer. While we expect contracted load to increase due to rising incomes, our study period also coincides with a dramatic increase in the availability of energy efficient lighting, in part due to government initiatives such as the Unnat Jyoti by Affordable LEDs for All (UJALA) program, which was launched on May 1, 2015.[8]. The overall reduction in contracted load that we observe in Table 1 reflects in part improvements in the efficiency of household appliance stocks. We observe changes in contracted load in about 29 percent of customer-years. While customers are on regular monthly billing cycles, for a variety of reasons the average customer-year is composed of about 9.89 bill observations. We observe some gaps in bills, likely reflecting customers deciding to pause their connection or facing a temporary disconnection due to non-payment, as well as customers' accounts lapsing due to their account closing and new connections. Throughout the analysis, we control for the number of billing days in each quarter of the year to control for the composition of billing cycles for each customer-year. Moreover, the outage values reflect the billing start and end dates at the customer-bill level.

During the study period, residential customers experienced about 2.64 h of outage per month. While the distribution of outage durations is strongly right-skewed, most customers faced regular outages. The median customer experienced about .88 h of outage per month, and only about 1.6 percent of customer-years experienced no outages. Reliability varies substantially across feeders of different customer mixes, reflecting the incentives of the utility to differentiate service quality according to the average prices paid

[7] India's 2014 national average consumption per connection from Centre for Policy Research and Prayas (2017). Trends in India's Residential Electricity Consumption: https://www.cprindia.org/news/6519; US average consumption per connection in 2017 from United States Energy Information Administration (2017): https://www.eia.gov/electricity/sales_revenue_price/pdf/table5_a.pdf.

[8] Over 13.3 million LED bulbs have been distributed in Delhi to date, yielding 1.725 TWh of energy savings per year according to engineering estimates produced by the Ministry of Power: http://www.ujala.gov.in/state-dashboard/delhi.

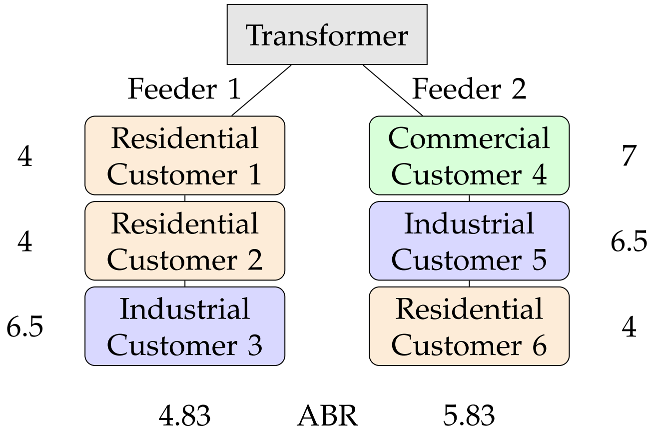

Fig. 1. Schematic of Average Billing Rate (ABR) formula.
The figure illustrates how feeder composition affects the Average Billing Rate (ABR) or the average revenue returned to the utility per kWh of electricity supplied to the feeder. The utility uses ABR to construct a priority ranking of feeders in order to guide decision-making on network investment, maintenance, and outage response. In this example, feeder 1 has two residential and one industrial customer, while feeder 2 has one commercial, one industrial and one residential customer. The average tariff rates, shown on either side of the schematic, vary based on the customer type. The higher proportion of high-tariff C&I customers on feeder 2 result in a higher ABR relative to that of feeder 1, as shown at the bottom of the schematic. The difference in ABR would imply that the residential consumer on feeder 2 may experience fewer outages than a residential consumer on feeder 1.

by different customer types. Figs. 5 and 6 plot monthly outage durations per customer at the feeder level by quartiles of the share of commercial and industrial customers and the average price paid on the feeder, respectively. At the outset of the study period, customers on feeders in the top quartile of the C&I share experienced about half the outage durations of customers on feeders in the bottom quartile. By 2019, this gap had narrowed substantially. Fig. 6 defines the quartiles by the average price paid for electricity on the feeder, which again reflect the mix of customer types served by the feeder as C&I customers face dramatically higher regulated tariffs. Because residential customers face a complex non-linear tariff structure, this measure also reflects the distribution of consumption within customer types on the feeder. Due to these non-linearities, the interquartile range in the average price paid for electricity by residential customers is about 2.49 INR per kWh, a factor of about two.

On average, households in the sample faced about 10 outages per month, with the average outage lasting about 3 h and 20 min. Outages are also seasonal, and both the mean number of outages and mean duration peak in June, July, and August. Outages were particularly prevalent in 2016, precipitating a series of efforts by the Delhi government to penalize the electricity distribution companies for poor reliability, which we discuss further in Section 3.5. Electricity reliability broadly improved in the years following 2016.

Figs. 7 to 12 plot responses of the surveyed households to questions concerning their electricity supply. Respondents report nighttime (8pm-midnight) to be the most common time for outages to occur, although that may be driven by the presence of more household members at home during that time. About 95 percent of respondents report being satisfied with the availability of supply. Almost 90 percent of respondents claim that all or most of the respondents in their area pay their electricity bill most or almost all of the time. More than 90 percent of respondents say that the most important reason why households in their area pay their electricity bill is either to avoid penalty or to avoid disconnection.

In the final section of our survey questionnaire, we asked households how they would trade-off different characteristics of electricity reliability, such as the duration, frequency and predictability of outages. Figs. 13–15 illustrate the responses of households to these choice experiments. The majority of households stated that they would prefer short outages spread over a longer duration (3 nights, 6 nights or 12 nights) compared to a longer continuous outage on a single night (see Fig. 13). The majority of households would prefer alonger anticipated outage to a shorter (i.e. 1-h) unanticipated outage regardless of whether the duration of the anticipated outage is 2, 3 or 4 h (see Fig. 14). Finally, the majority of households would prefer a longer outage in January to a shorter outage in June, but the share of households that prefer a 2-h outage in January to a 1-h outage in June is larger than the share of households that would prefer a 4-h outage in January to a 1-h outage in June, indicating a marginal effect of the duration of the outage (see Fig. 15).

Appendix Fig. A.1 plots the distribution of the cumulative wattage of appliances that each surveyed household owns. The median total wattage is 3 kW, which is equivalent to the median sanctioned load. Appendix Table A.5 lists the average wattage for common household appliances that we use to calculate the total wattage. To understand how much each appliance contributes to the household's total electric bill, we need to consider the wattage of the device and the length of time for which the device is used. For example, say an electric iron is used for 2 h and a hair dryer is used for 5 min. The iron consumes 2 kWh (1,000 W × 2 h) and the hair dryer consumes 0.125 kWh (1,500 W × 0.0833 h), which implies that using the iron costs roughly 16 times as much as the hair dryer.

Tables A.1 to A.4 summarize a variety of household and housing unit characteristics and appliance ownership statistics from the survey. On average, 11 percent of surveyed households live in rented accommodation and 20 percent live in multi-unit buildings.

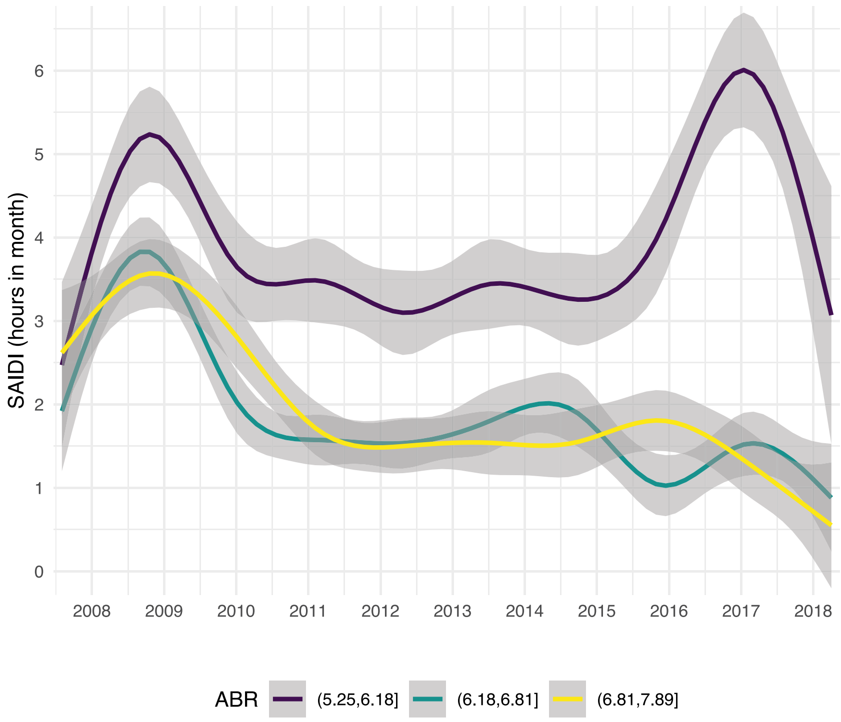

Fig. 2. Outages by Average Billing Rate (ABR) Terciles, 2007–2018.
The figure plots the System Average Interruption Duration Index (SAIDI) or the average hours of outage per month for each tercile of distribution of average billing rates across the zones within the distribution utility's service territory.

Almost all households use liquefied petroleum gas (LPG) for cooking and 45 percent receive treated drinking water. Furthermore, eight percent of surveyed households own power backups and eight percent share their electricity meter. About nine percent claim to have experienced appliance damage as a result of outages. Tables A.2 and A.3 provide counts of the number of appliances owned and the shares of each type that are connected to power backups, respectively. LED bulbs and ceiling fans are not only the most commonly-owned appliances, but they are also most likely to be backed up. Table A.4 summarizes total installed wattage and power backup ownership by education, occupation and income group. Total installed wattage and power backup ownership is consistently higher among more educated and higher income households.

2. Empirical strategy

We use an instrumental variables strategy to isolate plausibly exogenous variation in annual outage patterns. The causal relationship between outages and consumption is confounded through two principal channels. First, as discussed above, utilities effectively assign expected rates of reliability through their choices of where and when to ration power through blackouts and through levels of investment in grid capacity, maintenance, and outage response across their service territory. Highly differentiated tariff structures generate strong incentives for utilities to differentiate reliability across their customer base through these means, providing higher levels of reliability to higher-paying commercial and industrial customers than to lower-paying residential customers. Between 2015 and 2019, commercial and industrial customers served by the utility we study paid nearly double that of residential customers per unit of electricity. This figure refers to the unsubsidized tariff rate, defined as total billed charges, including fixed and variable charges, divided by the total billed kWh. Due to government subsidies for residential customers, the difference in the actual prices paid by these consumers is substantially larger. However, because Delhi's utilities are compensated for the subsidy burden, these subsidies should not directly affect their incentives. Fig. 16 plots the monthly average tariff rates for the four main customer categories: commercial, domestic, industrial, and informal settlement. Throughout the analysis, we group C&I customers and domestic and informal settlement customers, referring to the latter category as residential. Informal settlement customers face the same non-linear tariff structure and subsidies as residential customers.[9] Their lower tariff rates reflect lower levels of consumption as shown in the frequency distributions in Fig. 4. Historically, high rates of non-payment particularly among poorer customers have widened the gap in revenue returned per unit between commercial and industrial and residential customers,

[9] Informal settlement customers' connections to the grid were metered only after the Delhi government enacted power sector reforms in the late 1990s that partially privatized the distribution segment and introduced high-powered incentives for utilities to reduce losses.

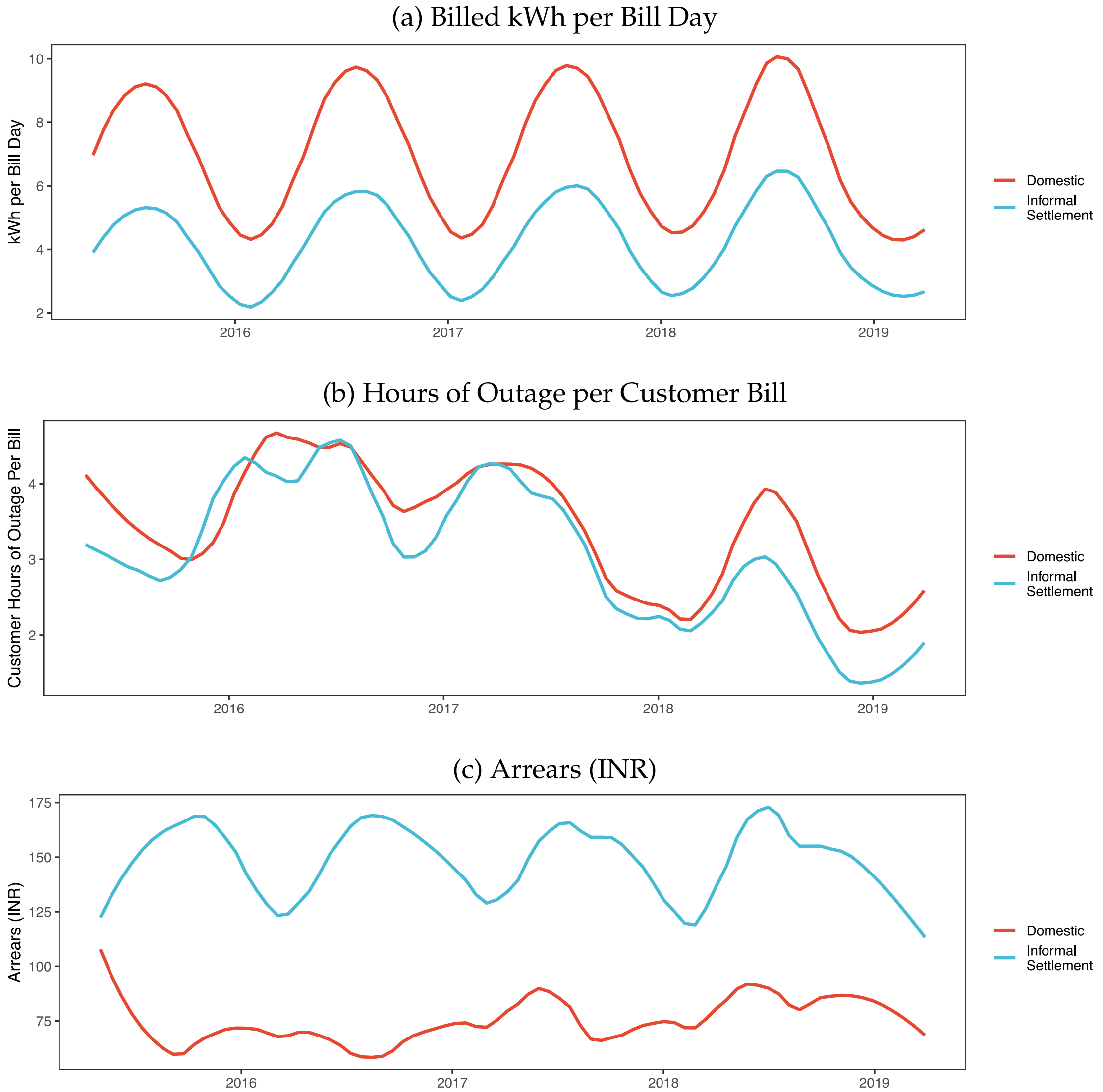

Fig. 3. Consumption, outages, and arrears by customer category, 2015–2019.
The figures plot locally estimated scatterplot smoothing (LOESS) regressions of billed kWh per bill day (a), hours of outage per customer bill (b), and arrears (c) on the end date of each customer's bill period for a sample of 100,000 domestic (red) and informal settlement customers (blue) for 2015 to 2019. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

distorting the incentive to differential reliability even further.[10] The assignment of lower levels of reliability to poorer residential customers through these mechanisms will likely generate a downward bias in the relationship between outages and consumption.

Second, both consumption and outages are likely to be correlated with idiosyncratic demand shocks. While utilities control expected outage patterns through rationing and investment decisions, stochasticity in outage realizations is driven primarily by weather events. In Delhi, the monsoon generally begins in late June or early July, and the rains often result in both rapid temperature fluctuations and winds and flooding that damage grid infrastructure. In addition to causing power outages in affected areas, these weather events likely also reduce electricity demand as temperatures fall and mitigate the need for air conditioning. On the other hand, outages may also be correlated with positive demand shocks. Each piece of infrastructure making up the distribution grid has

[10] On average, the annual bill payment rate (paid/amount payable) is 89% for domestic customers and 63% for informal settlement customers (Khanna and Rowe, 2022). While we do not have data on disconnections, we were informed by the utility that disconnection rules were rarely enforced during our sample period, largely because non-payment tended to be concentrated in informal settlement communities that have the backing of local politicians, making it harder for utility to disconnect these customers.

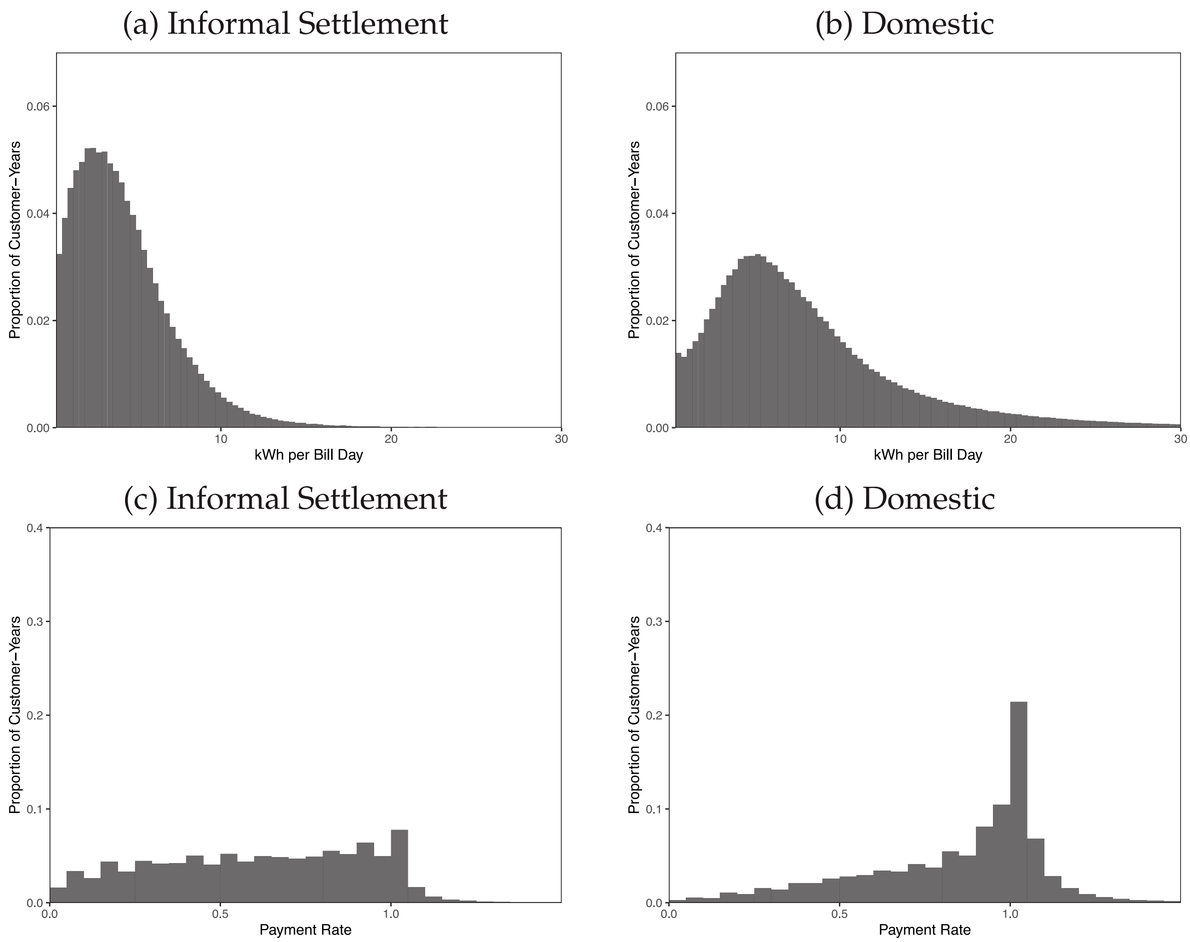

Fig. 4. Distribution of annual electricity consumption and payment rate, by customer category, 2015–2018.
The figure plots the distribution of billed electricity consumption in kWh per day and payment rate (paid/amount payable) by customer category during the study period.

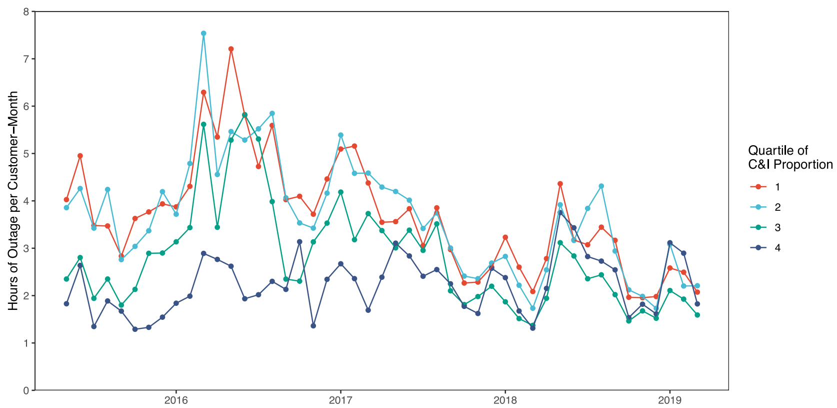

Fig. 5. Monthly hours of outage per customer by quartile of 2015 proportion of customers commercial and industrial (INR/kWh), 2015–2019.
The figure plots mean hours of outage per customer at the feeder-month level by quartiles of the proportion of customers on the feeder that are commercial and industrial in 2015.

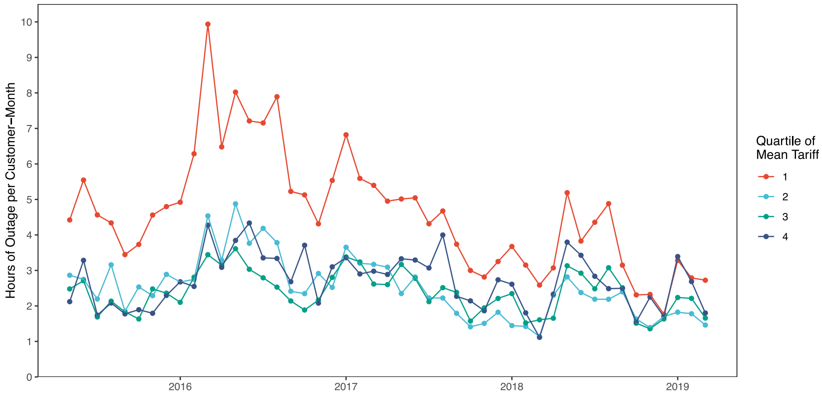

Fig. 6. Monthly hours of outage per customer by quartile of 2015 average tariff (INR/kWh), 2015–2019.
The figure plots mean hours of outage per customer at the feeder-month level by quartiles of 2015 average tariff. The average tariff is defined as the total bill amount, including all fixed and variable charges, divided by the total billed consumption in kWh.

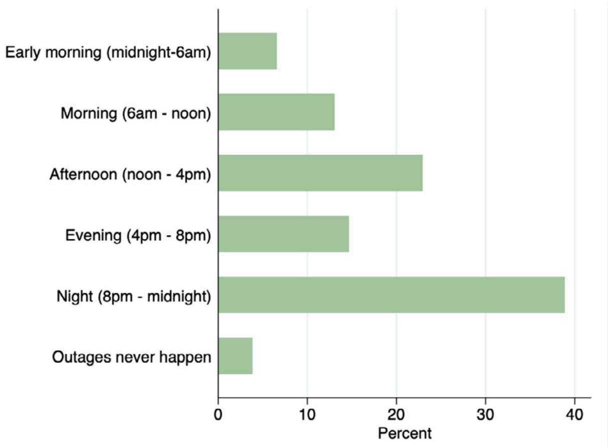

Fig. 7. Most common time when outages occur.
This figure plots surveyed households' responses to the following question: "Rank the times of day when power cuts are most common.".

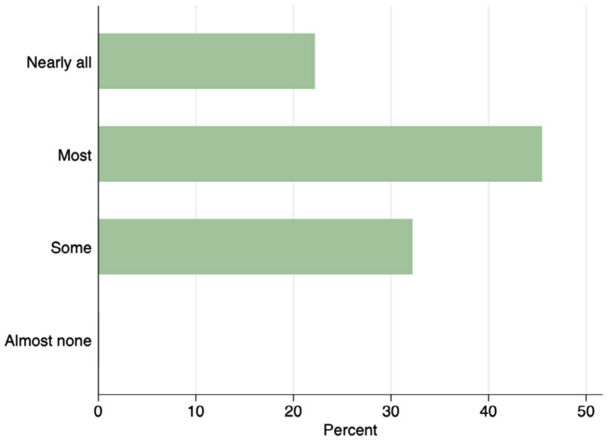

Fig. 8. Receiving alerts before outages
This figure plots surveyed households' responses to the following question: "For how many of the power outages experienced by the household does it receive advanced information?".

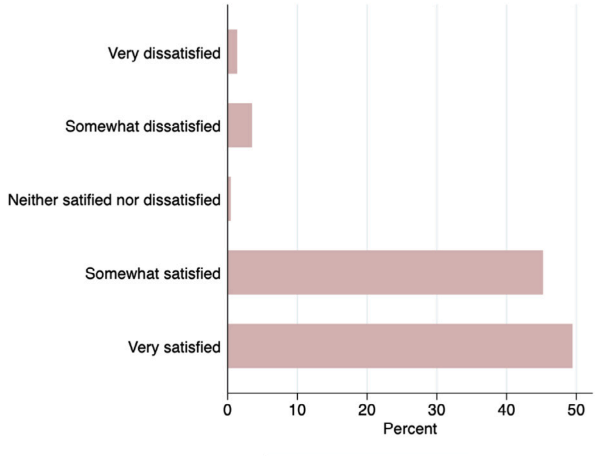

Fig. 9. Satisfaction with availability of supply.
This figure plots surveyed households' responses to the following question: ''How satisfied are you with the availability of electricity?''.

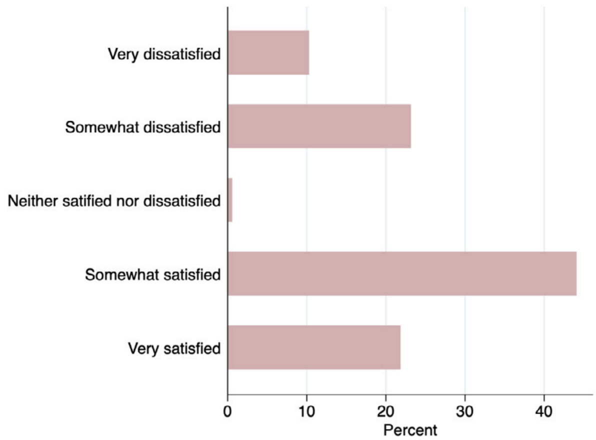

Fig. 10. Satisfaction with cost.
This figure plots surveyed households' responses to the following question: ''How satisfied are you with the cost of electricity?''.

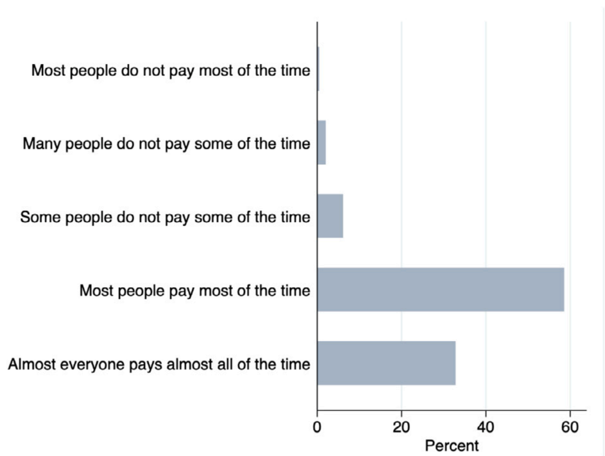

Fig. 11. Do people in the area pay their bills?
This figure plots surveyed households' responses to the following question: ''Based on what you know, do households in this area usually pay their electricity bills on time?''.

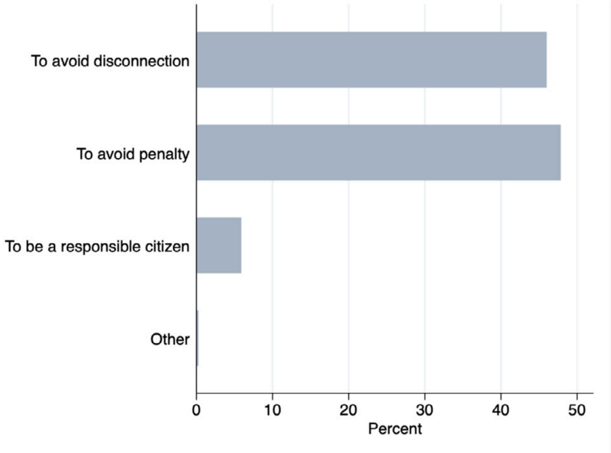

Fig. 12. Why do they pay their bills?
This figure plots surveyed households' responses to the following question: "What do you think people you know believe is the most important reason to pay their electricity bill on time?".

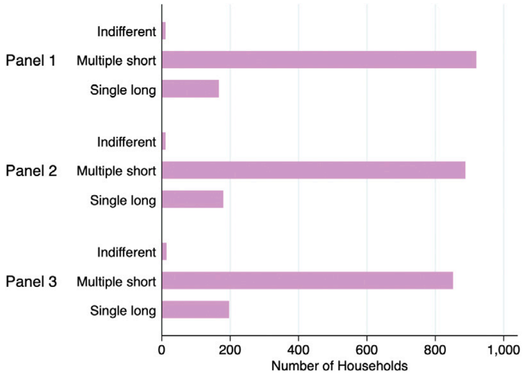

Fig. 13. Choice experiment: outage frequency.
The figure illustrates the responses of three randomly-selected groups of surveyed households that were asked whether they would prefer a single 3-hour outage between 7 and 10pm on one night or one of the following: three one-hour outages between 7 and 10pm on three different nights over the next two weeks (Panel 1), six half-hour outages between 7 and 10pm on six different nights over the next two weeks (Panel 2), or twelve quarter-hour outages between 7 and 10pm on twelve different nights over the next two weeks (Panel 3).

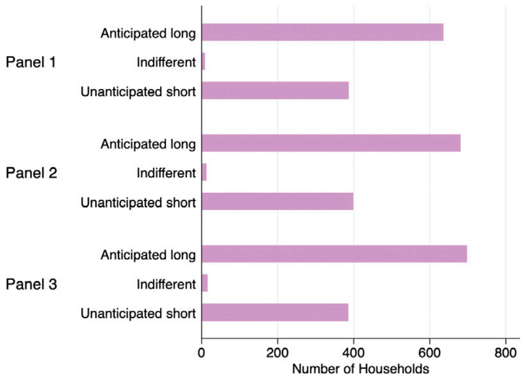

Fig. 14. Choice experiment: outage predictability.
The figure illustrates the responses of three randomly-selected groups of surveyed households that were asked whether they would prefer a 1-hour outage between 6 and 10 pm one night in the next few days with no prior notice or one of the following: a single 2-hour outage between 6 and 10pm one night in the next few days with an SMS from the electricity company on the morning the outage will occur (Panel 1), a single 3-hour outage between 6 and 10pm one night in the next few days with an SMS from the electricity company on the morning the outage will occur (Panel 2), or a single 4-hour outage between 6 and 10pm one night in the next few days with an SMS from the electricity company on the morning the outage will occur (Panel 3).

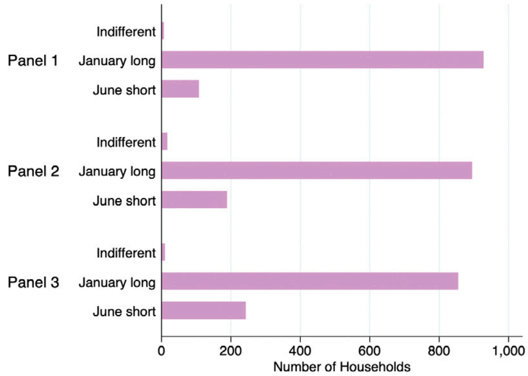

Fig. 15. Choice experiment: outage timing.
The figure illustrates the responses of three randomly-selected groups of surveyed households that were asked whether they would prefer a 1-hour outage between 6 and 10pm in June or one of the following: a 2-hour outage between 6 and 10pm in January (Panel 1), a 3-hour outage between 6 and 10pm in January (Panel 2), or a 4-hour outage between 6 and 10pm in January (Panel 3).

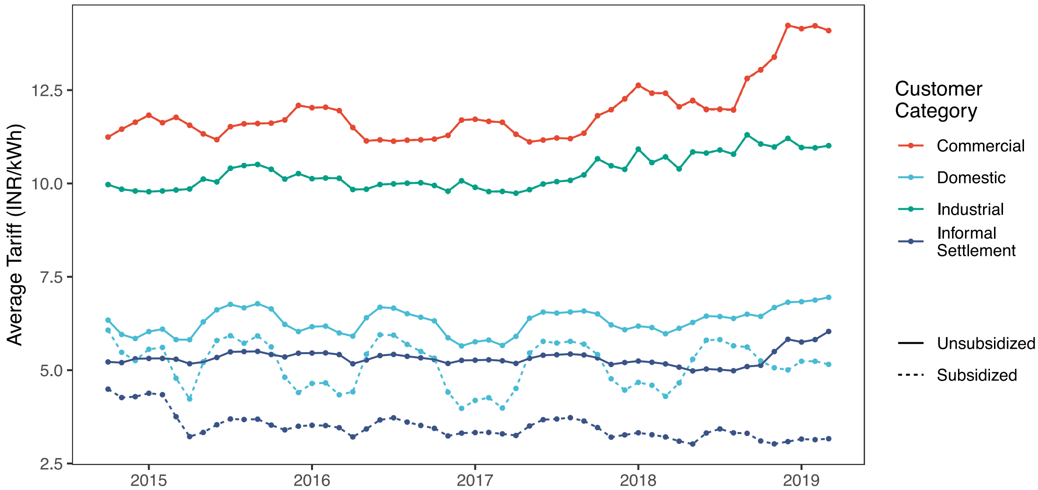

Fig. 16. Average subsidized and unsubsidized tariff (INR/kWh) by customer category, 2014–2019.
The figure plots monthly subsidized and unsubsidized average total tariff in INR per kWh by major customer categories for 2014 to 2019. The average total tariff is defined as the total bill amount, including all fixed and variable charges, divided by the total billed consumption in kWh. Unsubsidized tariffs exclude subsidies that are reimbursed to the utilities by the Delhi government. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a capacity limitation, and attempts to withdraw power exceeding the capacity of the lines and transformers will result in equipment failures and power outages. Hence positive demand shocks, for instance due to sustained high temperatures resulting in high demand for air conditioning, increase the probability of overloading. Heat stress from high temperatures can also increase other types of equipment failures in the grid when demand for electricity is highest. As a consequence, comparisons of consumption patterns for customers facing differing frequencies of power outages may be confounded by demand shocks that are correlated with outage realizations. As the examples suggest, correlated demand shocks could bias the relationship between outages and consumption in either direction.

While utilities face strong incentives to differentiate service quality, grid technology limits the granularity at which they are able to do so. The utility we study measures and manages reliability at the distribution feeder level. During the period of study, the utility's approximately 1,100 feeders served between one and 7,608 customers and many comprised heterogeneous sets of customers. Feeders are the lowest level at which the utility centrally conducts load shedding, the practice of curtailing availability of electricity to sections of its service territory in response to a potential inability to serve demand. Feeders are also the lowest level of the network at which the utility has comprehensive statistics on reliability.[11] Moreover, the utility generates a priority ranking of

[11] Due to the recent rollout of advanced metering technologies, the utility is able to observe customer-level outage statistics for a growing share of its customer base. During the period studied, these customers were limited to commercial and industrial customers and large residential customers (with contracted loads of greater than 10 kW) not included in the estimation sample.

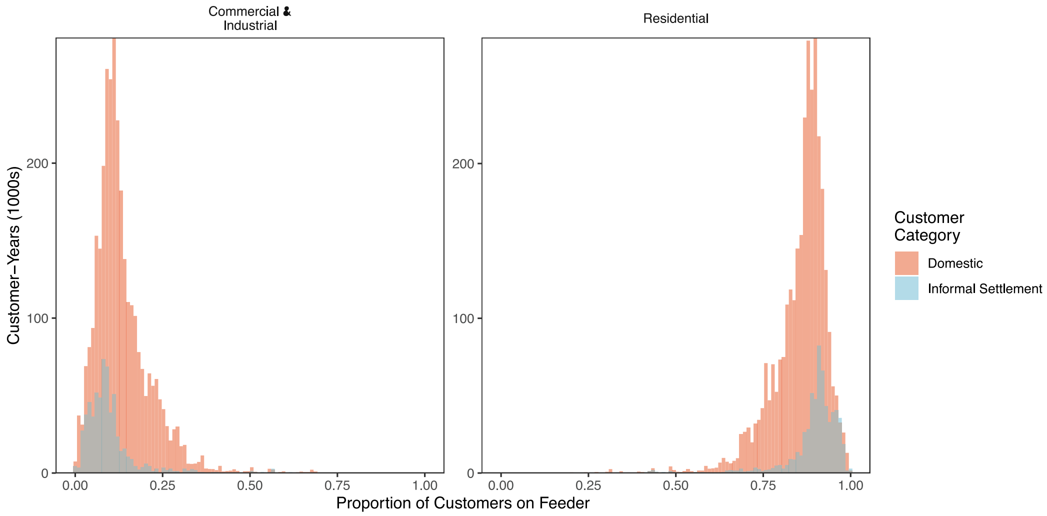

Fig. 17. Distributions of the proportion of customers on feeder for domestic and informal settlement customers, 2015–2019.
The figure plots the distributions of the composition of customers on feeders during the study period. The histograms are generated from customer-year observations, with domestic customers plotted in red and informal settlement customers plotted in blue. The left figure plots the distributions of commercial and industrial customers on the feeder, and the right figure plots the distributions of residential customers on the feeder. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

feeders according to the Average Billing Rate (ABR) or the average revenue per unit (i.e., the average tariff), which it uses for decision-making on network investment, maintenance, and outage response. For feeders with a mix of residential and commercial customers, the average revenue rate reflects the mix of customers on the feeder. Fig. 1 illustrates through a hypothetical example how the composition of customers on the feeder affects the ABR of the feeder when the regulated tariff regime differentiates pricing across customer types. These differences in ABR could generate plausibly exogenous variation in the level of electricity reliability experienced by residential customers on feeders with different proportions of commercial and industrial customers. In the example, feeder 1 has two residential customers and one industrial customer, while feeder 2 has one commercial customer, one industrial customer and one residential customer. Since the average tariffs vary based on the customer type, the higher share of high-tariff commercial and industrial customers on feeder 2 pushes up its ABR relative to that of feeder 1. The difference in ABR implies that a residential customer on feeder 2 may experience fewer outages than a residential customer on feeder 1, all else equal. Fig. 2 provides evidence that the utility uses ABR for allocating outages across feeders. Outage durations fell by more than 60 percent for customers on feeders in the top two-thirds of ABR between 2007 and 2018, while customers in the bottom third of ABR saw only modest improvements in reliability during this period and faced about 2.5 h of outage on average each month. This gap in reliability between the customers paying the most and those paying the least was a key motivation prompting Delhi's regulators to introduce outage compensation policies in 2017. Fig. 17 plots the distributions of C&I and residential shares for the feeders serving domestic and informal settlement customers.

Our instrumental variables strategy takes advantage of feeder-level variation in average revenue rates to compare similar customers across feeders that experience differing reliability trends as a result of their differing customer compositions. The utility's incentive to differentiate reliability across feeders based on their customer compositions will increase when the gap between the regulated tariffs paid by C&I and residential customers widens as that would further drive up the average revenue that the utility can expect to earn by supplying an additional unit of electricity to a feeder with a higher proportion of C&I customers. Therefore, the instrument we construct, $z_{f,t}$, is the interaction between the proportion of the customers served by each feeder that are commercial or industrial at the beginning of the study period in 2015, $c_{f,2015}$, and the annual utility-wide aggregate difference between the average revenue rate of commercial and industrial and residential customers, $p_{c,t} - p_{r,t}$:

$$z_{f,t} = c_{f,2015} \cdot (p_{c,t} - p_{r,t}), \tag{1}$$

where f indexes feeders, c indexes commercial and industrial customers, r indexes residential customers, and t indexes years. For each feeder, the C&I 2015 share is:

$$c_f = \frac{1}{n_{f,2015}} \sum_{i \in I_f} \mathbf{1}_c, \tag{2}$$

where I_f is the set of unique customers receiving at least one bill on feeder f in financial year 2015, and $\mathbf{1}_c$ is an indicator function for customer i being categorized as commercial or industrial, and $n_{f,2015}$ is the number of unique customers on the feeder in 2015.

The aggregate time-varying price differential is the difference between the average C&I and residential tariffs, where the average tariffs are defined by:

$$p_{c,t} = \left[\sum_{i=1}^{I} b_{i,t} \cdot \mathbf{1}_c\right]\left[\sum_{i=1}^{I} e_{i,t} \cdot \mathbf{1}_c\right]^{-1}, \qquad p_{r,t} = \left[\sum_{i=1}^{I} b_{i,t} \cdot \mathbf{1}_r\right]\left[\sum_{i=1}^{I} e_{i,t} \cdot \mathbf{1}_r\right]^{-1}. \tag{3}$$

In the equation, $b_{i,t}$ is the total billed amount in INR for customer i in year t, including all fixed and variable charges, and $e_{i,t}$ is the total billed consumption in kWh. Note that because the tariff schedule is highly non-linear, $p_{c,t}$ and $p_{r,t}$ incorporate variation from tariff policy changes as well as variation in aggregate consumption levels.

The first stage estimating equation is

$$o_{i,f,t} = \alpha z_{f,t} + X'\beta + \gamma_i + \gamma_t + \varepsilon_{i,f,t}, \tag{4}$$

where $o_{i,f,t}$ is the average hours of outage on feeder f during customer i's billing periods in financial year t (from April to the following March), X is a vector of covariates, γ_i and γ_t are customer and year fixed effects, and $\varepsilon_{i,y}$ is an error. The second stage regresses the log total billed units in the year on the predicted hours of outage from the first stage:

$$e_{i,f,t} = \sigma\hat{o}_{i,f,t} + X'\delta + \gamma_i + \gamma_t + \eta_{i,t}. \tag{5}$$

While average tariffs are observable at the feeder level, the non-linearity in the tariff structure means the realized average tariff at the feeder level is correlated with consumption, and hence is correlated with the demand shocks that also confound outages. This is visible in Fig. 16, which shows that, particularly for domestic and informal settlement customers, average tariffs vary seasonally as customers reach higher steps on the increasing block tariff. The instrument takes advantage of both cross-sectional and time series variation in the utility's incentives differentiate reliability across feeders but is orthogonal to feeder-year demand shocks by construction. We also control for feeder-level average consumption, the number of bills issued to customers on the feeder, and the mean tariff on the feeder to absorb potential feeder-year level demand shocks.

The instrument's exclusion restriction requires that the initial composition of the feeder, or the cross-sectional component of the instrument, affects electricity consumption only through its effect on outages Goldsmith-Pinkham et al. (2020). To verify that the instrument satisfies the exclusion restriction, we show that the composition of customers on the feeder is not correlated with characteristics of residential customers that predict electricity consumption, such as household income.

3. Results

3.1. Main results

Table 2 presents the main estimates of consumption responses to outages at the customer-year level. Columns 1 and 2 report OLS estimates with and without customer and year fixed effects, respectively, column 3 reports the first stage, and column 4 reports the IV estimate. Across the specifications, we control for the feeder-year covariates mentioned above, as well as customer-year covariates, including the customer's mean tariff and the number of billing days in each quarter of the year. We control for the number of billing days in each quarter because a sizeable share of customers included have gaps in their billing cycles. Throughout the analysis, we report standard errors clustered at the feeder level. In column 1, an additional hour of outage per month is associated with about a 1.45 percent reduction in billed kWh during the course of the year. Adding customer and year fixed effects to this specification in column 2 renders the estimated effect indistinguishable from zero and not statistically significant.

Column 3 reports the first stage. The estimated coefficient on the instrument, the annual tariff gap interacted with the feeder's 2015 C&I customer share is negative, −4.030. Aside from the modest variation in outages introduced by differences in customers' billing periods, the first stage operates primarily at the feeder-year level. The estimation sample for the IV, the subset of the utility's 1100 feeders that serve at least two residential customers and for which all of the outage data are available, includes 654 feeders. The first stage Kleibergen–Paap Wald F statistic is 14.85, and we report Anderson–Rubin weak instrument robust confidence sets for all the IV estimates (Anderson and Rubin, 1949; Andrews et al., 2019).

Column 4 reports the IV estimate: an additional hour of outage per month causes about a 4.8 percent reduction in annual billed consumption. To place the magnitude of this estimate into context, the table also reports the average hours of outage per month for the estimation sample, which is 2.75. An additional hour of outage per month is equivalent to about a 36 percent increase relative to the mean. The estimate has a t statistic of 3.85 and the Anderson-Rubin weak instrument robust 95 percent confidence set rejects zero.

Column 5 reports the IV estimate on changes in sanctioned load, which serves as a proxy for household appliance stocks. An important caveat here is that a lower sanctioned load may reflect a more efficient appliance stock, rather than simply a smaller one, and so we cannot fully separate the information on size and efficiency contained in this measure. The estimate suggests that an additional hour of outage per month reduces sanctioned load by 0.41 kW annually.

We consider the magnitude of the effect to be large and interpret it in terms of two potential channels. The first channel is short-run: outages prevent affected consumers from consuming grid-served electricity during the time of the outage. Outages are highly correlated with both seasonal and diurnal patterns of electricity demand. Through the course of the year, monthly residential customer demand fluctuates by about 2.5-fold between the trough in December and the peak in June or July. Particularly for customers with small appliance stocks, the intra-day fluctuation may be even greater in magnitude. As seen in Fig. 3, these patterns

Table 2
Consumption (log kWh per day) on hour of outage per customer per month, 2015–2018.

	OLS		IV		
	log billed kWh per day	log billed kWh per day	First stage: Outage hours	log billed kWh per day	IV: Change in load (KW)
	(1)	(2)	(3)	(4)	(5)
Mean Outage Hours per Month	−0.0144***	−0.000745		−0.0474***	−0.410***
	(0.00234)	(0.000517)		(0.0123)	(0.104)
CI-residential tariff gap × Proportion CI in 2015			−4.030***		
			(1.046)		
Feeder billed kWh per day	0.00132**	−0.0000382	0.0360**	0.00193**	−0.00719
	(0.000633)	(0.000146)	(0.0140)	(0.000864)	(0.00568)
Mean tariff in year on feeder (INR/kWh)	0.0334**	0.0311***	0.0643	0.0250	0.377***
	(0.0131)	(0.00422)	(0.328)	(0.0158)	(0.140)
Bills on feeder in year (1000s)	−0.00509***	0.00155***	−0.0306	0.0000156	−0.00291
	(0.000721)	(0.000195)	(0.0230)	(0.00117)	(0.00918)
Mean tariff in year (INR/kWh)	−0.0119***	−0.0141***	0.00127***	−0.0143***	−0.000811***
	(0.000576)	(0.000875)	(0.000354)	(0.000940)	(0.000248)
Bill days in Q1	0.000136	−0.00106***	0.0123***	−0.000243	0.00291
	(0.000109)	(0.0000301)	(0.00419)	(0.000286)	(0.00222)
Bill days in Q2	0.00538***	0.00378***	0.00443	0.00377***	−0.00965***
	(0.000155)	(0.0000643)	(0.00336)	(0.000162)	(0.00128)
Bill days in Q3	0.00496***	0.00551***	−0.00117	0.00561***	0.00613***
	(0.000163)	(0.0000967)	(0.00291)	(0.000173)	(0.00115)
Bill days in Q4	0.0178***	0.00843***	−0.00533***	0.00807***	−0.00232***
	(0.000240)	(0.000153)	(0.00145)	(0.000189)	(0.000856)
Constant	−0.761***	0.0907***	4.554**		
	(0.0957)	(0.0315)	(2.043)		
Customer FEs		✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Mean Tariff Gap			4.579	4.579	4.574
Mean Outages	2.640	2.640	2.756	2.756	2.791
Mean kWh per Day	7.666	7.666	7.744	7.744	7.381
Observations	3 350 052	3 350 052	2 888 276	2 799 612	2495794
Clusters	848	848	667	654	651
First Stage F Statistic				14.85	14.52
Anderson–Rubin Statistic				102.0	86.06
Anderson–Rubin 95% CI				[−.092623, −.031383]	[−.779273, −.270614]
R^2	0.223	0.256	0.0589	0.183	−1.278

The table reports OLS (columns 1 and 2) and instrumental variables (3, 4, and 5) regression estimates of consumption in log kWh per day (4) and contracted load (5) on customer hours of outage per month at the financial year level for 2015 to 2018. Financial years begin in April and end in March of the following calendar year. Standard errors are clustered at the feeder level.

coincide with those of outages: during the study period, average customer hours of outages across feeders peaked in the early summer at about 1.5-fold that of the trough in winter. As a result, the average outage likely affects hours with consumption that is well-above the annual mean. On the other hand, consumers may also substitute some consumption to earlier or later time periods in response to outage realizations, mitigating the magnitude of the consumption reduction due to outages. The utility we study notifies customers about planned outages by SMS, and about 36 percent of the customers surveyed reported ever receiving alerts from the utility.

A second channel operates in the mid- to long-run as consumers adapt their consumption patterns in response to their expectations about outages. When outages are more frequent, we expect consumers to shift their demand for energy services away from electricity, reducing consumption not only in response to individual outage realizations but throughout the year even when outages are not realized. These responses might take a variety of forms, including using existing appliances less and slowing purchases of new appliances.

Frequent outages may also prompt households to invest in backup diesel generators or batteries to ensure continuity of supply. Electricity from these off grid sources tends to be very expensive. In addition to the capital and maintenance costs associated with the devices themselves, the variable cost of most residential-scale diesel generator setups is more than double that of the grid-served tariff per kWh at recent regulated diesel prices in Delhi. While batteries do not require fuel input, common battery technologies often have efficiencies of around 80 percent, meaning that each kWh stored makes only about .8 kWh available for later consumption. For households that value continuity of supply, the fixed and variable costs of backups effectively raises the average cost of electricity. It is conceivable that these households would respond to the effective cost of electricity, reducing consumption relative to households facing less frequent outages and thus having lower average costs of ensuring continuous supply. This channel is difficult to investigate for the entire customer base using the utility's data, though our survey did ask a variety of questions on backup power ownership. We find that about 8 percent of households had either a backup generator or battery installed.

Table 3
Domestic customers: Consumption (log kWh per day) on hour of outage per customer per month, 2015–2018.

	OLS		IV		
	log billed kWh per day	log billed kWh per day	First stage: Outage hours	log billed kWh per day	IV: Change in load (KW)
	(1)	(2)	(3)	(4)	(5)
Mean outage hours per customer per month	−0.0180*** (0.00240)	−0.00105* (0.000596)		−0.0401*** (0.0112)	−0.451*** (0.121)
CI-residential tariff gap × Proportion CI in 2015			−4.033*** (1.111)		
Feeder billed kWh per day	0.00125** (0.000567)	0.0000537 (0.000148)	0.0333** (0.0138)	0.00160** (0.000749)	−0.00804 (0.00645)
Mean tariff in year on feeder (INR/kWh)	0.0800*** (0.00784)	0.0333*** (0.00449)	−0.109 (0.313)	0.0227* (0.0132)	0.373** (0.154)
Bills on feeder in year (1000s)	−3.084*** (0.521)	1.403*** (0.198)	−24.09 (22.94)	0.345 (0.963)	−0.222 (10.21)
Mean tariff in year (INR/kWh)	−0.0118*** (0.000559)	−0.0134*** (0.000826)	0.00148*** (0.000376)	−0.0135*** (0.000888)	−0.000809*** (0.000293)
Bill days in Q1	0.000468*** (0.0000867)	−0.000986*** (0.0000319)	0.0105*** (0.00369)	−0.000359 (0.000222)	0.00282 (0.00225)
Bill days in Q2	0.00535*** (0.000137)	0.00374*** (0.0000692)	0.00366 (0.00324)	0.00369*** (0.000134)	−0.0113*** (0.00134)
Bill days in Q3	0.00528*** (0.000155)	0.00580*** (0.000109)	0.000827 (0.00284)	0.00599*** (0.000163)	0.00821*** (0.00128)
Bill days in Q4	0.0180*** (0.000269)	0.00874*** (0.000160)	−0.00534*** (0.00155)	0.00843*** (0.000195)	−0.00287*** (0.00103)
Constant	−1.063*** (0.0653)	0.120*** (0.0321)	5.667*** (1.979)		
Customer FEs		✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Mean Tariff Gap			4.578	4.578	4.572
Mean Outages	2.651	2.651	2.776	2.776	2.820
Mean kWh per Day	8.280	8.280	8.401	8.401	7.989
Observations	2 805 221	2 805 221	2 401 057	2 324 818	2087193
Clusters	836	836	655	639	635
First Stage F Statistic				13.17	12.92
Anderson–Rubin Statistic				71.53	88.36
Anderson–Rubin 95% CI				[... , −.025465]	[... , −.291269]
R^2	0.253	0.256	0.0554	0.206	−1.354

The table reports OLS (columns 1 and 2) and instrumental variables (3 and 4) regression estimates of consumption in log kWh per day on customer hours of outage per month at the financial year level for domestic customers from 2015 to 2018. Financial years begin in April and end in March of the following calendar year. Standard errors are clustered at the feeder level.

3.2. Responses of domestic and informal settlement customers

Tables 3 and 4 present the IV estimates separately for domestic and informal settlement customer, respectively. Doing so further limits the number of feeders in the samples, particularly for informal settlement customers, leaving the instrument weaker. As a result, we interpret these estimates more cautiously. Comparing the IV estimates in column 4 of each table, the response of informal settlement customers to outages appears to be substantially larger in magnitude that of domestic customers.

A portion of this difference is likely explained by the short-run channel. Informal settlement customers may lose more consumption to the average hour of outage as compared with domestic customers because their intraday electricity demand patterns are more variable and highly coincident with outages. During the study period, average consumption per day for informal settlement customers was about 54 percent of that of domestic customers. This difference reflects both lower ownership rates of appliances among informal settlement customers and also different usage patterns. In the survey of customers, differences in appliance ownership between domestic and informal settlement customers were largest for appliances that often run continuously for much of the day or night, like ceiling fans, refrigerators, and air conditioners. The most commonly owned appliances for informal settlement customers, including lighting, televisions, box fans, and phone charges, are primarily used on demand and particularly in the evening when outages are most common. Moreover, while refrigerators and air conditioners may automatically ramp up following an outage to return to a temperature set point, much of the consumption from lighting, televisions, and fans is difficult to replace with later consumption if the power is out when these services are demanded.

The difference in the responsiveness in consumption to outages between informal settlement and domestic customers may also be attributable in part to differential rates of backup power ownership. Ownership of backup power among domestic customers in the

Table 4
Informal settlement customers: Consumption (log kWh per day) on hour of outage per customer per month, 2015–2018.

	OLS		IV		
	log billed kWh per day	log billed kWh per day	First stage: Outage hours	log billed kWh per day	IV: Change in load (KW)
	(1)	(2)	(3)	(4)	(5)
Mean outage hours per customer per month	−0.0114**	0.00105		−0.0843***	−0.114***
	(0.00443)	(0.000663)		(0.0318)	(0.0378)
CI-residential tariff gap × Proportion CI in 2015			−4.633**		
			(1.865)		
Feeder billed kWh per day	0.00298***	−0.00154*	0.0828**	0.00612	−0.00294
	(0.000861)	(0.000911)	(0.0415)	(0.00389)	(0.00356)
Mean tariff in year on feeder (INR/kWh)	−0.0716***	0.0156**	0.854	0.0652	0.0753
	(0.0120)	(0.00700)	(0.642)	(0.0538)	(0.0647)
Bills on feeder in year (1000s)	−1.981	2.448***	−56.27	−2.705	−3.940
	(1.465)	(0.401)	(40.85)	(3.994)	(4.404)
Mean tariff in year (INR/kWh)	−0.0589***	−0.0418***	−0.00229	−0.0418**	−0.00190***
	(0.0122)	(0.0156)	(0.00241)	(0.0164)	(0.000480)
Bill days in Q1	−0.000488**	−0.00142***	0.0197**	0.000677	0.000212
	(0.000231)	(0.0000522)	(0.00860)	(0.00100)	(0.00110)
Bill days in Q2	0.00394***	0.00377***	0.0106	0.00440***	−0.00359***
	(0.000271)	(0.000106)	(0.00708)	(0.000594)	(0.000644)
Bill days in Q3	0.00402***	0.00421***	−0.0103*	0.00346***	−0.000276
	(0.000311)	(0.000293)	(0.00599)	(0.000571)	(0.000532)
Bill days in Q4	0.0121***	0.00589***	−0.00565**	0.00531***	0.000258
	(0.00103)	(0.000773)	(0.00238)	(0.000816)	(0.000338)
Constant	0.213	0.126	−0.501		
	(0.190)	(0.160)	(3.878)		
Customer FEs		✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Mean Tariff Gap			4.584	4.584	4.583
Mean Outages	2.584	2.584	2.654	2.654	2.643
Mean kWh per Day	4.503	4.503	4.510	4.510	4.277
Observations	544 831	544 831	487 219	474 670	408 551
Clusters	458	458	390	382	373
First Stage F Statistic				6.170	6.237
Anderson–Rubin Statistic				56.59	16.87
Anderson–Rubin 95% CI				[... , −.047792]	[... , −.060768]
R^2	0.240	0.295	0.0912	0.0167	−0.264

The table reports OLS (columns 1 and 2) and instrumental variables (3 and 4) regression estimates of consumption in log kWh per day on customer hours of outage per month at the financial year level for informal settlement customers from 2015 to 2018. Financial years begin in April and end in March of the following calendar year. Standard errors are clustered at the feeder level.

survey was about ten-fold that of informal settlement customers, and the difference is nearly as large after conditioning on income. While the overall rate among surveyed customers was low, around 7 percent, we believe that backup power ownership rates were likely underestimated by our survey.[12] The consumption of customers that own backup power may be less sensitive to outages. For customers with battery inverters, which make up nearly all of the backup units observed in the survey, this relationship is in part mechanical, as the battery enables users to charge when grid power is available and discharge when the power is out. For these consumers, the battery will compensate for outages by charging more frequently when outages are more frequent.

3.3. Instrument validity and robustness

We draw on our household survey results to test the instrument's exclusion restriction. Our empirical strategy draws on comparisons of similar customers across feeders with different compositions. As such, it relies on a degree of balance in the residential customer base across feeders with differing C&I shares. For example, if higher income consumers are on feeders with higher C&I shares, we may worry that outages are being driven by other factors, such as the quality of non-electricity infrastructure. Fig. 18 plots predicted values and standard errors from two separate regressions of the 2015 and 2018 C&I share of each feeder's customer base on

[12] Backups such as diesel generators and battery inverters are often shared among multiple households, particularly in apartment buildings, in which case they may be kept outside the household, making it possible that the survey respondent was not aware that they do use a backup in the event of an outage. Furthermore, the survey respondent might have also confused ownership with usage since the utilization of backups has conceivably reduced given the marked improvement in electricity reliability over the last decade in Delhi.

Table 5
Customer and feeder characteristics on income, surveyed customers, 2015–2019.

	Customer level				Customer-year level		
	Installed Watts	Informal settlement (=1)	Proportion C & I, 2015	Proportion C & I, 2018	Outage hours per month	Billed kWh per day	Average tariff (INR/kWh)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[0, 25,000]	−1143.3***	0.245*	−0.0191**	−0.0177***	−1.109	−1.772**	−0.0324
	(347.2)	(0.139)	(0.00808)	(0.00681)	(0.741)	(0.686)	(0.200)
(25,000, 50,000]	−490.7***	0.0535	0.00604	0.00155	0.796	−0.0706	0.0733
	(120.1)	(0.0619)	(0.00817)	(0.00637)	(0.544)	(0.391)	(0.110)
(50,000, 75,000]	−360.4***	0.0461	−0.00725	−0.00670	−0.0259	−0.203	0.0860
	(95.25)	(0.0364)	(0.00502)	(0.00411)	(0.354)	(0.216)	(0.0883)
(150,000, 300,000]	776.4***	−0.0832**	0.00807	0.00461	−0.0481	0.819***	0.130
	(126.4)	(0.0348)	(0.00556)	(0.00446)	(0.374)	(0.215)	(0.0791)
(300,000, 500,000]	1753.6***	−0.221***	0.0352**	0.0218*	−0.265	1.250***	0.311***
	(253.9)	(0.0475)	(0.0146)	(0.0119)	(0.507)	(0.414)	(0.0982)
> 500,000	1989.4***	−0.255***	0.0297	0.0176	−2.432***	2.925***	0.570***
	(724.1)	(0.0724)	(0.0195)	(0.0145)	(0.531)	(0.473)	(0.154)
Constant	2507.5***	0.398***	0.108***	0.102***	3.455***	5.932***	3.416***
	(77.08)	(0.0441)	(0.00687)	(0.00541)	(0.439)	(0.187)	(0.0490)
Observations	2175	2361	1864	2296	7886	7886	7886
Clusters	175	203	151	196	203	203	203
R^2	0.108	0.0244	0.0156	0.00781	0.00456	0.0220	0.00273

The table reports regression estimates at the customer level (columns 1–4) and customer-year level (5–7) for surveyed customers. The outcome is shown in the column title and the regressors are indicator variables for the annual income bins corresponding to the survey questionnaire. For all specifications, the omitted category is the middle income bin, INR 75,000 to 150,000. Standard errors are clustered by distribution feeder.

Table 6
Derivation of the value of lost load (VoLL).

	Domestic	Informal settlement	All residential
A: Estimated elasticity of consumption with respect to average price	−1.427	−1.118	−1.412
B: Mean tariff (INR/kWh)	4.4855	3.6498	4.3438
C: Mean kWh per day	7.541	3.916	6.926
D: Estimated change in mean hourly consumption (kWh) per 1 INR/kWh increase in price	−0.1	−0.05	−0.09
E: Estimated % change in annual consumption peradditional hour of outage per month	−4.01	−8.43	−4.76
F: Mean outage duration (hours per customer-month)	2.776	2.654	2.755
G: Estimated elasticity of consumption with respect to hours of outage	−0.11	−0.22	−0.13
H: Estimated change in mean hourly consumption per unit increase in outage duration	−10.13	−11.48	−11.18
I: Willingness to pay (INR) to avoid 1 kWh of lost consumption	101.3	229.6	124.22

This table reports derived estimates of the value of lost load (VoLL) or the willingness to avoid 1 kWh of lost electricity consumption for domestic and informal settlement customers using estimates of the consumption response to outages as well as estimates of price elasticities of demand from the same setting (Khanna and Rowe, 2022).

income bins for surveyed customers. Table 5 presents these results in a regression, along with the correlations between income and additional characteristics from the bills and survey. The omitted category in these regressions is the income bin extending from INR 75,000 to INR 150,000 per year. Columns (1) and (2) show that income is positively correlated with installed wattage and negative correlated with residing in an informal settlement respectively. Importantly, while income is a strong predictor of consumption (Column 6) and the average tariff (Column 7), we do not observe a correlation between income and the composition of the feeder that the customer is connected to (Columns 3 and 4), which lends support for our identification assumption. Customers with income greater than INR 500,000 per year, which accounts for 1.4% of households who reported income on the survey, experience fewer outage hours per month relative to those earning between INR 75,000 to INR 150,000 per year, but we do not see a relationship across the rest of the income distribution.

3.4. Revealed preference estimates of the value of lost load

Planning investments in the electricity sector requires having an understanding of households' willingness to pay (WTP) for electricity reliability (Deustschmann et al., 2021). In Table 6, we combine our empirical estimates of long-run price elasticities of demand from the same setting (Khanna and Rowe, 2022) with our estimates of the consumption response to outages to derive a revealed preference measure of the VoLL for domestic and informal settlement customers. Specifically, the process for calculating the VoLL proceeds in three steps. First, we calculate the estimated change in mean daily consumption associated with a one INR/kWh increase in the average price (row D) by dividing the mean kWh per day (row C) by the mean tariff (row B) and multiplying by

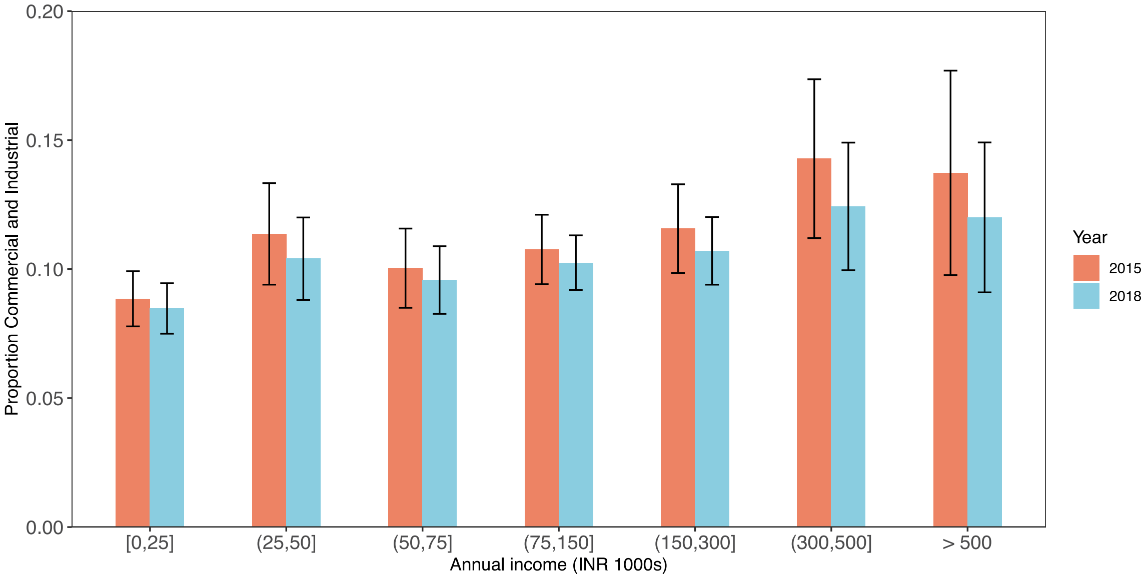

Fig. 18. Proportion of commercial and industrial customers on feeder in financial years 2015 and 2018, by annual household income.
The figure plots the predicted values and 95 percent confidence intervals from separate regressions of proportion of customers on feeder that are commercial or industrial in 2015 (red) and 2018 (blue) for customers surveyed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

our estimated price elasticity of demand (row A). Second, we calculate the estimated change in mean daily consumption associated with a unit increase in outage duration (row H) by dividing the mean kWh per day by the mean outage duration (row F) per customer-hour and multiplying by the elasticity of consumption with respect to outage duration (row G). Lastly, we divide the long-run change in consumption per unit change in outage duration (row H) by the change in consumption per unit change in price (row D) to obtain the marginal WTP to avoid one kWh of lost consumption (row I). This implied VoLL can be interpreted as the change in the electricity price that would trigger a reduction in consumption equivalent to the amount that would be reduced annually as a result of a unit increase in outage duration. Our VoLL estimates of INR 124.22 per kWh (USD 1.50 per kWh) suggest that households would be willing to pay more than 25 times the average tariff to avoid one kWh of lost consumption. If household electricity demand during an outage period is equal to the annual mean, the loss in consumer surplus would amount to 10% of the average monthly bill, but this share rises to 27% if we assume, perhaps more realistically, that household electricity demand during outage periods is 2.5 times the annual mean. These VoLL estimates for residential consumers are significantly greater than recent stated preference estimates from developing countries. Alberini et al. (2022) use a contingent valuation survey to estimate a VoLL in the range of 5 to 15 NR per kWh (USD .05 to 0.14 kWh) for domestic customers in Nepal. In comparison, our estimates are closer to those found in some high-income countries. In a study prepared for the UK electricity regulator, the Office of Gas and Electricity Markets (OFGEM), choice experiments were used to elicit domestic consumers' willingness to pay to avoid an electricity outage. The study found estimates in the range of USD 2.16 per kWh to USD 3.62 per kWh (Economics, 2013). The large estimates of the VoLL we find in our setting are driven by the large long-run effects of outages on electricity consumption that we find in this paper.

3.5. Policy implications

Our estimates of the VoLL for residential customers help inform the ongoing debate in India on incentivizing improvements in electricity reliability. In September 2017, the Delhi Electricity Regulatory Commission (DERC) required that the city's regulated electricity distribution utilities pay compensation to customers experiencing power outages of three hours or longer, a measure that was intended to incentivize the utilities to invest in infrastructure and management practices needed to deliver higher service quality. Delhi's compensation policy directly counteracts the adverse incentive to differentiate service quality based on the price customers pay. Because of the cross-subsidies in Delhi's regulated electricity prices, serving one kWh to commercial customers in Delhi returns more than three times as much revenue to the utilities than does serving one kWh to residential customers. As a result, the utilities are strongly incentivized to maintain higher levels of reliability to these higher paying customers. By requiring utilities to pay per customer, the outage compensation policy does not privilege higher paying customers. Fig. 19 shows that reliability improved most among lower paying residential customers following the implementation of the 2017 policy. The improvements were greatest in

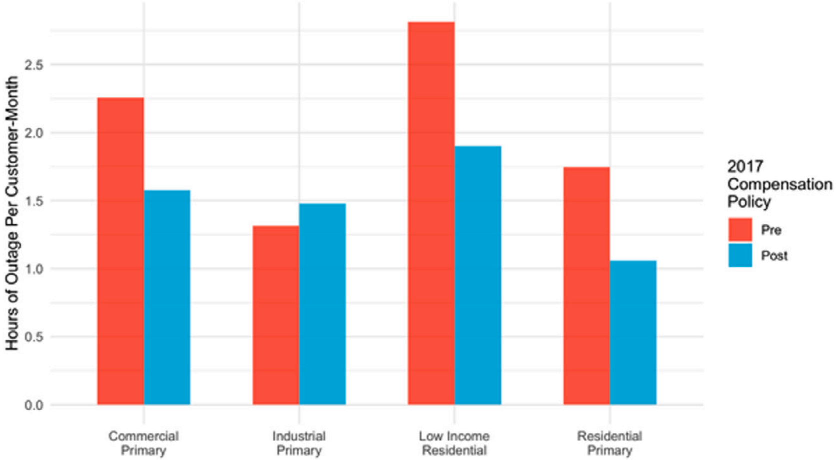

Fig. 19. Mean hours of outage by feeder customer composition before and after 2017 outage compensation policy.
The figure plots the mean hours of outage faced by customers on primarily commercial, primarily industrial, low income residential and primarily residential feeders before (red) and after (blue) the enactment of the 2017 DERC Supply Code that required distribution utilities to compensate customers for unplanned outages. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

areas with more informal settlement customers, who are generally very poor. The right to claim compensation for power outages was recently expanded to all citizens under the Electricity (Rights of Consumer) Rules, 2020 (Government of India, 2020).

While such policies would likely induce utilities to reprioritize investments and maintenance decisions, the financial implications for utilities that are already burdened with debt could be substantial. For many utilities, outage compensation policies would make the already stark choice between serving the most subsidized consumers at a loss or conducting rolling blackouts only starker. The additional financial losses that accrue as a result would need to be made up either by state budgets or future rate increases on electricity customers. For these reasons, outage compensation policies are unlikely to resolve tradeoff between prices and quality in India's electricity distribution sector. Doing so relies critically on optimizing retail pricing so that it provides an allocation rule for delivering electricity to those who value it the most. The large estimated VoLL we find in this paper suggests that increasing prices and reliability for residential consumers would be welfare-improving provided that the utility can provide reliability more cheaply than behind-the-meter solutions such as backup generators and battery inverters. We anticipate that our estimate of the VoLL could inform consultations between utilities and regulators on the design of retail pricing policies and can be directly applied in cost–benefit analysis on grid reliability-enhancing investments such as in transmission and distribution infrastructure.

4. Conclusion

In this paper, we find that an additional hour of outage per month reduces annual electricity consumption by 4.8%, which when combined with our estimated price elasticities of demand, correspond to an annual VoLL of USD 1.50 per kWh. The large magnitude of these estimates suggest that residential consumers in Delhi are willing to pay more than 25 times the average retail price during outage periods to avoid the outage.

At present, regulated retail tariffs that charge rates well-above the average cost of supply to businesses while keeping power prices below the average cost of supply for households are justified as a means to make electricity more affordable to the poor. However, such rate structures disincentivize utilities from improving quality of service for poor customers and extending access to unelectrified communities, which often results in a low-price, low-quality equilibrium. For several decades, economists have urged that retail tariffs for electricity be set at a level that would allow utilities to recover their costs. Instead of reducing prices for the poor, they argue governments should offer direct benefit transfers to consumers who cannot afford to pay their bills.

However, "getting the price right" in order to be able to ensure 24x7 power supply for every customer may not be socially efficient if the value of electricity reliability is heterogeneous across and within types of customers. Therefore, we emphasize the need to estimate the value of electricity reliability so as to inform the tradeoff between affordability and reliability that regulators face in designing retail rates as well as demand response programs. Utilities contract a large amount of generation capacity to meet their anticipated demand during a few hours in the year, which results in a substantially higher average cost of supply that gets socialized through the tariff structure. Knowing when customers value electricity the most could help design tariffs in a way that allows utilities to optimize their power procurement decisions. Optimization to mitigate supply–demand imbalances is becoming increasingly important as the share of intermittent renewable energy on the grid rises, for which understanding how the VoLL varies by the timing of the outage, the duration, season, the type of customer affected, and whether the outage was anticipated or not, will be important. Finally, non-payment serves as an additional tax to the extent that the unrecovered costs from commercial losses are rolled into retail tariffs, which highlights the importance of understanding the bill payment response to long-term improvements in electricity reliability. Further research on these topics could deliver an even more granular understanding of the VoLL, which could help policymakers and regulators design electricity markets that efficiently cater to the level of electricity reliability consumers demand.

CRediT authorship contribution statement

Shefali Khanna: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Kevin Rowe:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data availability

The data that has been used is confidential.

Appendix

A.1. Figures

See Fig. A.1.

A.2. Tables

See Tables A.1–A.6.

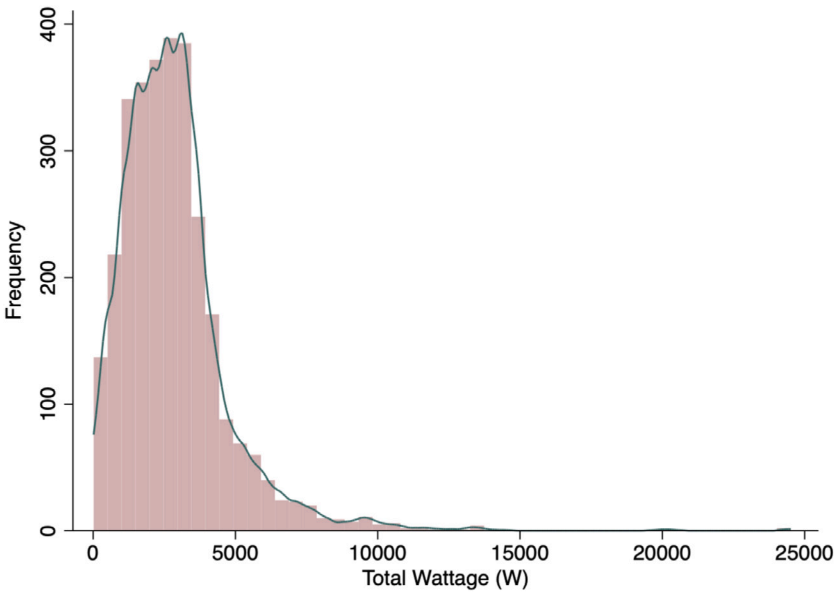

Fig. A.1. Household survey summary statistics: Total installed wattage.
This figure plots the distribution of the total installed wattage. Total installed wattage is calculated using the average wattage of common household appliances and the number of each type of appliance that households claim to own.

Table A.1
Household survey summary statistics: Household characteristics.

	Responses	Mean	Median	Minimum	Maximum	Standard deviation
Number of adults	3288	2.94	3	0	16	1.86
Number of children	3288	1.68	2	0	14	1.48
Rented home	3290	.11	0	0	1	.31
House price (INR)	494	339 682.1	65 000	0	10 000 000	784 872.9
Rent amount (INR)	329	4216.64	3500	0	75 000	4599.07
Electricity bill (INR)	3217	810.27	500	1	12 000	898.27
Number of rooms	3283	2.3	2	0	12	1.28
Multi-unit building	3290	.2	0	0	1	.4
Number of units	652	2.99	2	0	15	2.01
Number of stories	658	2.71	3	0	8	1.12
Run business from home	3287	.12	0	0	1	.33
Use LPG for cooking	3290	1	1	0	1	.05
Treat drinking water	2576	.45	0	0	1	.5
Heat water	3289	.71	1	0	1	.45
Heat house	3284	.02	0	0	1	.14
Have solar	3288	0	0	0	1	.02
Have backup	3277	.08	0	0	1	.27
Share electricity meter	3285	.08	0	0	1	.28
Receive information about power cuts	3124	.36	0	0	1	.48
Appliance damage due to power cuts	3290	.09	0	0	1	.28
Outages per month in the summer	3277	5.31	4	0	90	5.3
Outages per month in the monsoon	3265	4.37	3	0	61	4.21
Outages per month in the winter	3246	2.79	2	0	60	3.43

This table reports the number of responses and summary statistics of household and housing unit characteristics and perceptions about electricity reliability.

Table A.2
Household survey summary statistics: Number of appliances owned.

Appliance	Responses	Mean	Median	Minimum	Maximum	Standard deviation
Incandescent bulbs	3290	.06	0	0	4	.31
Tubelights	3290	1.03	1	0	25	1.43
CFL bulbs	3290	.37	0	0	15	1.01
LED bulbs	3289	2.93	3	0	25	2.37
Flashlights	3290	.04	0	0	4	.22
Radios	3290	.12	0	0	2	.33
VCR/DVD players	3290	.02	0	0	1	.15
Food processors	3290	.54	1	0	3	.5
Freestanding fans	3290	.57	1	0	5	.65
Electric irons	3290	.64	1	0	7	.51
Hair dryers	3290	.04	0	0	2	.19
Sewing machines	3290	.01	0	0	8	.17
Rice cookers	3290	0	0	0	1	.07
Air coolers	3290	.81	1	0	5	.69
Smartphone chargers	3289	1.55	1	0	17	1.17
Regular phone chargers	3289	.76	1	0	5	.73
Toasters	3289	.02	0	0	3	.16
Electric ovens	3289	.03	0	0	10	.29
Printers	3289	.01	0	0	2	.11
Vacuum cleaners	3289	0	0	0	1	.06
Ceiling fans	3289	2.35	2	0	35	1.69
Televisions	3008	.98	1	0	6	.5
Air conditioners	3289	.21	0	0	4	.5
Electric water heaters	3288	.09	0	0	3	.3
Electric space heaters	3289	.01	0	0	2	.11
Refrigerators	3289	.79	1	0	3	.45
Microwave ovens	3289	.02	0	0	1	.13
Washing machines	3289	.47	0	0	3	.51
Computers	3288	.1	0	0	3	.32
Electric generator sets	3290	0	0	0	1	.02
Battery inverters	3290	.07	0	0	2	.26
Voltage regulators	3091	.08	0	0	8	.35

This table reports the number of affirmative responses and summary statistics of number of appliances owned by the type of appliance.

Table A.3
Household survey summary statistics: Appliances connected to power backups.

Appliance	Responses	Mean	Median	Minimum	Maximum	Standard deviation
Incandescent bulbs	7	.43	0	0	1	.53
Tubelights	150	.83	1	0	1	.38
LED bulbs	216	.93	1	0	1	.25
CFL bulbs	49	.76	1	0	1	.43
Radios	38	.13	0	0	1	.34
VCR/DVD players	13	.31	0	0	1	.48
Food processors	170	.16	0	0	1	.37
Freestanding fans	124	.27	0	0	1	.45
Ceiling fans	233	.94	1	0	1	.24
Electric irons	186	.16	0	0	1	.36
Hair dryers	21	.05	0	0	1	.22
Rice cookers	6	.17	0	0	1	.41
Sewing machines	3	.33	0	0	1	.58
Air coolers	129	.19	0	0	1	.39
Smartphone chargers	222	.79	1	0	1	.41
Regular phone chargers	110	.67	1	0	1	.47
Toasters	24	.04	0	0	1	.2
Electric ovens	24	.13	0	0	1	.34
Vacuum cleaners	4	.25	0	0	1	.5
Televisions	172	.23	0	0	1	.42
At least one air conditioner	134	.02	0	0	1	.15
At least one electric water heater	75	.01	0	0	1	.12
At least one electric space heater	7	0	0	0	0	0
At least one refrigerator	219	.04	0	0	1	.19
At least one microwave oven	19	.05	0	0	1	.23
At least one washing machine	198	.04	0	0	1	.19
At least one computer	58	.19	0	0	1	.4

This table reports the number of affirmative responses and summary statistics of number of appliances connected to power backup by the type of appliance.

Table A.4
Household survey summary statistics: Cumulative wattage, power backups and demographics.

	Total wattage of household appliances					Have power backup		
	Responses	Mean	SD	Minimum	Maximum	No.	Col %	Row %
Education level of household head								
Never been to school	469	2446.8	1538.6	20.0	20 338.0	14	9.9	2.8
Standard I	2	4358.0	2203.3	2800.0	5916.0	0	0.0	0.0
Standard II	13	2931.5	1897.1	290.0	7610.0	0	0.0	0.0
Standard III	10	2267.8	1377.3	380.0	4410.0	0	0.0	0.0
Standard IV	27	2209.4	1449.9	100.0	5280.0	0	0.0	0.0
Standard V	210	2593.3	1517.3	90.0	10 320.0	12	8.5	5.3
Standard VI	40	2459.1	1696.4	120.0	9618.0	1	0.7	2.2
Standard VII	47	2680.6	1420.4	100.0	7250.0	4	2.8	8.2
Standard VIII	157	2646.1	1589.0	100.0	9474.0	6	4.2	3.5
Standard IX	54	2920.6	2270.7	110.0	13 413.0	1	0.7	1.8
Standard X	343	3221.0	1816.1	90.0	10 555.0	30	21.1	8.1
Standard XI	20	3677.1	1218.3	1424.0	5880.0	3	2.1	15.0
Standard XII	208	3664.0	2359.8	90.0	19 896.0	32	22.5	14.2
Diploma	4	3202.0	2385.6	700.0	6348.0	3	2.1	60.0
Bachelors continue/incomplete	7	2951.9	1282.1	1445.0	5245.0	1	0.7	14.3
Completed Bachelors	85	4799.7	2849.4	370.0	13 020.0	26	18.3	25.5
Post-graduation continue/incomplete	3	5436.7	2105.5	3870.0	7830.0	1	0.7	33.3
Completed post-graduation	20	4461.2	2846.9	100.0	12 474.0	8	5.6	34.8
Total	1719	2970.5	1938.3	20.0	20 338.0	142	100.0	7.7
Primary occupation of household head								
Housewife	140	3053.3	1889.7	140.0	11 820.0	6	4.2	4.0
Animal Husbandry	2	2282.5	1587.5	1160.0	3405.0	0	0.0	0.0
Self-employed	442	3139.8	2187.9	20.0	19 896.0	40	27.8	8.4
Works on own farm	13	3668.3	1020.6	1654.0	5350.0	4	2.8	28.6
Casual farm labor	11	2073.3	950.8	738.0	3408.0	1	0.7	9.1
Casual non-farm labor	218	2078.6	1259.7	90.0	9240.0	97.0	7	4.9
Salaried worker	623	2978.0	1819.8	100.0	12 474.0	49	34.0	7.2
Retired (without pension)	36	4835.8	2844.2	600.0	13 315.0	9	6.2	24.3
Pensioner	91	3554.9	1748.0	600.0	11 430.0	11	7.6	10.9
Cannot work due to old age or disability	155	3058.6	2147.2	110.0	20 338.0	15	10.4	9.1
Unemployed and looking for work	9	2762.6	1292.2	1280.0	4590.0	0	0.0	0.0
Unemployed and NOT looking for work	8	2571.5	1575.0	730.0	5550.0	2	1.4	25.0
Total	1748	2983.9	1957.8	20.0	20 338.0	144	100.0	7.6
Annual household income								
0 to 25,000 INR	15	1803.3	1522.2	284.0	4730.0	0	0.0	0.0
25,000 to 50,000 INR	174	2033.4	1238.8	90.0	6730.0	9	4.3	4.6
50,000 to 75,000 INR	486	2198.3	1401.3	90.0	10 852.0	21	10.0	4.0
75,000 to 150,000 INR	1156	2559.5	1684.4	20.0	24 510.0	54	25.7	4.3
150,000 to 300,000 INR	634	3368.7	2153.4	90.0	20 338.0	75	35.7	11.0
300,000 to 500,000 INR	152	4188.5	2491.4	110.0	14 315.0	43	20.5	24.6
500,000 to 1,000,000 INR	37	4600.7	2762.0	380.0	11 820.0	5	2.4	12.8
More than 1,000,000 INR	1	6334.0		6334.0	6334.0	3	1.4	100.0
Total	2655	2771.0	1908.1	20.0	24 510.0	210	100.0	7.3

The table reports the number of affirmative responses, estimated installed wattage, and power backup ownership statistics by education level, primary occupation of the household head and annual household income categories.

Table A.5
Appliance wattage.

Appliance	Watts
Incandescent bulbs	75
Tubelights	40
CFL bulbs	14
LED bulbs	10
Flashlights	5
Radios	30
VCR/DVD players	40
Food processors	390
Electric irons	1000
Hair dryers	1500
Sewing machines	75
Rice cookers	700

(*continued on next page*)

Table A.5 (*continued*).

Appliance	Watts
Air coolers	180
Smartphone chargers	10
Regular phone chargers	0
Toasters	1150
Electric ovens	2150
Printers	800
Vacuum cleaners	1200
Ceiling fans	80
Televisions	500
Air conditioners	750
Electric water heaters	1500
Electric space heaters	900
Refrigerators	500
Microwave ovens	1400
Washing machines	500
Computers	60

The table reports average wattage values for common household appliances in India, which we collected from various websites that provide information on energy consumption to consumers.

Table A.6
Consumption (log kWh per day) on hour of outage per customer per month, 2015–2018.

	OLS		IV		
	log billed kWh per day	log billed kWh per day	First stage: Outage hours	log billed kWh per day	IV: Change in load (KW)
	(1)	(2)	(3)	(4)	(5)
Mean outage hours per customer per month	−0.0144***	−0.000745		−0.0511***	−0.401***
	(0.00234)	(0.000517)		(0.0134)	(0.106)
CI-residential tariff gap × Proportion CI			−4.135***		
			(1.110)		
Feeder billed kWh per day	0.00132**	−0.0000382	0.0407***	0.00229**	−0.00728
	(0.000633)	(0.000146)	(0.0157)	(0.00103)	(0.00575)
Mean tariff in year on feeder (INR/kWh)	0.0334**	0.0311***	0.133	0.0245	0.389***
	(0.0131)	(0.00422)	(0.304)	(0.0153)	(0.126)
Bills on feeder in year (1000s)	−5.087***	1.550***	−1.388	1.301	9.865
	(0.721)	(0.195)	(18.57)	(0.974)	(7.311)
Mean tariff in year (INR/kWh)	−0.0119***	−0.0141***	0.00117***	−0.0140***	−0.000832***
	(0.000576)	(0.000875)	(0.000331)	(0.000868)	(0.000226)
Bill days in Q1	0.000136	−0.00106***	0.0100***	−0.000326	0.00191
	(0.000109)	(0.0000301)	(0.00365)	(0.000262)	(0.00188)
Bill days in Q2	0.00538***	0.00378***	0.000922	0.00363***	−0.0108***
	(0.000155)	(0.0000643)	(0.00301)	(0.000160)	(0.00115)
Bill days in Q3	0.00496***	0.00551***	0.00183	0.00574***	0.00698***
	(0.000163)	(0.0000967)	(0.00263)	(0.000174)	(0.00108)
Bill days in Q4	0.0178***	0.00843***	−0.00527***	0.00810***	−0.00219***
	(0.000240)	(0.000153)	(0.00136)	(0.000188)	(0.000811)
Constant	−0.761***	0.0907***	3.381*		
	(0.0957)	(0.0315)	(1.881)		
Customer FEs		✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Mean Tariff Gap			4.620	4.620	4.616
Mean Outages	2.640	2.640	2.655	2.655	2.688
Mean kWh per Day	7.666	7.666	7.653	7.653	7.300
Observations	3 350 052	3 350 052	3 297 546	3 070 170	2732036
Clusters	848	848	817	732	726
First Stage F Statistic				13.87	13.52
Anderson–Rubin Statistic				113.1	4.217
Anderson–Rubin 95% CI				[−.102545, −.033656]	[−35.5153, −1.04281]
R^2	0.223	0.256	0.0446	0.173	−1.205

The table reports OLS (columns 1 and 2) and instrumental variables (3, 4, and 5) regression estimates of consumption in log kWh per day (4) and contracted load (5) on customer hours of outage per month at the financial year level for 2015 to 2018. Financial years begin in April and end in March of the following calendar year. Standard errors are clustered at the feeder level.

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