Essays in Energy and Development Economics

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Essays in Energy and Development Economics

A dissertation presented

by

Kevin Rowe

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Essays in Energy and Development Economics

Abstract

The three essays in this dissertation investigate the economic and policy challenges of providing access to reliable and affordable electricity in India. Across much of the country, regulated retail electricity prices enable agricultural and residential consumers to buy power at a fraction of the cost of supplying it to them. Forced to sell electricity at a loss to broad segments of their customer base, state-owned electricity distribution companies often resort to rationing electricity through rolling blackouts, a practice referred to as "load shedding." Chapter 1 evaluates the welfare and distributional implications of retail electricity price subsidies and the rationing that accompanies it for customers served by India's largest electricity distribution utility, the Maharashtra State Electricity Distribution Company Limited (MSEDCL), in 2017 and 2018. It begins by documenting how MSEDCL uses peak load shedding to curtail its costs of wholesale power purchase, estimating that in 2017 and 2018 on average the company shed load for an additional approximately 246,000 people in response to a one standard deviation increase in its marginal cost of energy. The paper then develops a dynamic structural model of electricity demand under quantity rationing in order to evaluate the welfare loss to customers from power outages and their willingness to pay for higher levels of reliability. Estimating the model using an original dataset of hourly electricity consumption on 16,633 power lines served by MSEDCL, I find that the welfare losses from power outages in 2017 and 2018 for the categories of customers facing severe rationing of power were equivalent to those of increases in the marginal electricity price ranging between about 20 to 70 percent.

Chapter 2, which is coauthored with Shefali Khanna, estimates the short- and long-run responses of retail electricity consumption and bill payment to electricity prices in Delhi, India from 2015 to 2019. Using billing data from one of Delhi's three private electricity distribution utilities, we reconstruct payment histories for more than 1.5 million retail residential, commercial, and small industrial customers. Our empirical strategies exploit features of the regulated electricity price schedule that generate short- and long-run variation in the average price of electricity for these customers. In addition to providing annual price elasticity estimates, we find evidence that non-payment rates increase when prices rise. The effects are particularly large for the poorest informal customers, for whom arrears more than double in response to a doubling in the average electricity price.

Finally, Chapter 3, which is also coauthored with Shefali Khanna, 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 about 4.85 percent.

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Chapter 1

The Welfare and Distributional Implications of Non-Price Rationing of Electricity in India

1.1 Introduction

Frequent power outages are a nearly universal experience for Indian retail electricity consumers. Rural populations in India's poorest states are often subjected to more than 10 hours a day of blackouts (Aklin et al., 2016). Poor electricity reliability persists in spite of what appears to be a substantial surplus of electricity generation capacity nationally and recent progress toward relieving many of the most acute capacity shortages and inefficiencies on the grid (Parray and Tongia, 2019).

This paper analyzes power outages in India as a short-run quantity rationing mechanism, rather than an outcome of poor infrastructure quality or grid capacity constraints. Retail electricity prices are a salient issue in state and local politics across much of India, and many states use the regulated electricity price schedule as a means of redistribution (Mahadevan, 2019; Burgess et al., 2020). In Maharashtra, India's second largest state by population, regulated retail prices for agriculture and below poverty line households recover less than half of the state-owned distribution utility's cost of supplying these customers with electricity (Maharashtra Electricity Regulatory Commission, 2016). In turn, the utility subjects these consumers to severe rationing: agricultural consumers in the state faced outages for more than 2.5 hours per day on average in 2017. In contrast, large industrial and commercial customers paid dramatically higher prices for their electricity and faced less than 5 percent of the average outage duration of agricultural customers. Figure 1.1 illustrates this stark relationship between the marginal price of electricity (shown on the right axis and the ranges) and the frequency of power outages (shown in the left axis and the blue bars) across customer categories in Maharashtra in 2017.

Here I investigate the welfare and distributional implications of retail electricity price subsidies when they are accompanied by rationing through blackouts, a practice referred to as "load shedding." First, I provide evidence that India's largest state-owned electricity distribution utility, Maharashtra State Electricity Company Limited (MSEDCL), engages in rationing as a means of cost control. Using an instrumental variables strategy, I show that in hours when MSEDCL faces idiosyncratically higher costs of wholesale electricity procurement, it engages in more severe rationing. In particular, in 2017 the utility shed load to an additional approximately 246,000 people in response to a one standard deviation increase in the marginal cost of wholesale electricity on average. This evidence supports the hypothesis that, at least in Maharashtra, a central focus in improving reliability should be on the incentives generated by the prices facing regulated utilities in both the wholesale and retail markets.

Next I turn to the responses of MSEDCL's customers to frequent power outages. In this section, I provide descriptive evidence suggesting that the agricultural and rural residential customers that face the most severe rationing also have the most adaptive consumption patterns among the customer categories, enabling them to mitigate much of the effect of an outage by shifting consumption to other periods, at least in the short run. On the other hand, these results also show that large industrial and commercial customers are far less adaptive, meaning that they are generally poorly equipped to mitigate the effect of an outage by shifting their consumption through time.

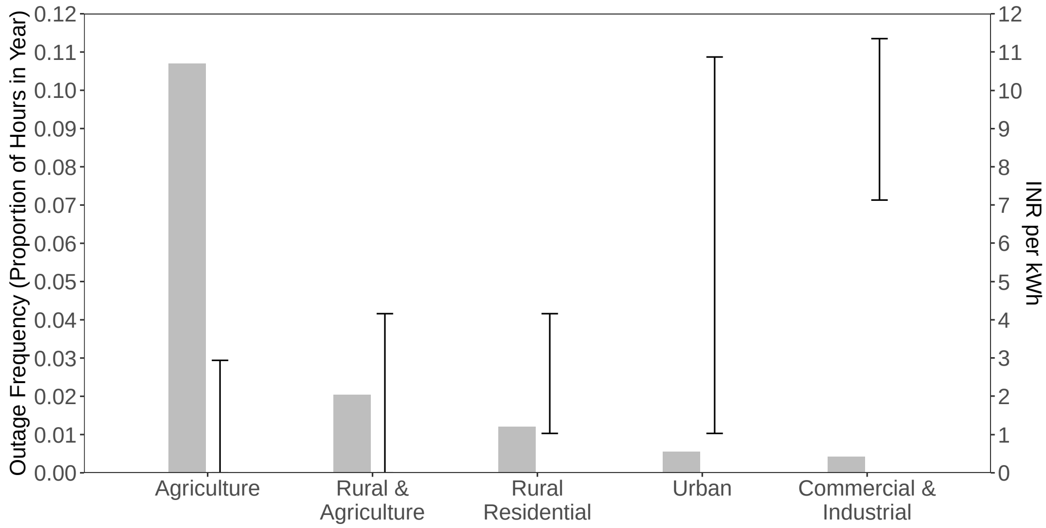
This evidence motivates the paper's dynamic structural model of electricity demand under non-price rationing. The model represents the welfare loss associated with a power outage as a constraint away from the consumer's optimal path of electricity consumption through time. Consistent with the heterogeneity in responses revealed in the descriptive results, the model accommodates the possibility of either intertemporal substitutability or complementarity in consumption through time. In the case of intertemporal substitutability, a portion of the welfare loss from power outages can be mitigated by consuming at times during which power is available. On the other hand, in the case of intertemporal complementarity, the welfare loss from outages may propagate into periods after the power is restored. I estimate the model across MSEDCL's customer categories in order to evaluate the extent to which poor reliability undermines the value of generous subsidies through the electricity price schedule. I find that for residential customers facing the most severe rationing, the welfare loss from power outages for one month in 2017 and 2018 was about equivalent to that from increasing the marginal electricity price by about 20 to 70 percent.

The range of welfare losses reflects heterogeneity in the value of reliability, the severity of outages, and the regulated prices across customer categories. I find that for agriculture, the most subsidized and most severely rationed category, the welfare loss from an hour per month of additional outage duration is equivalent to that of about a 1 percent increase in the price. In contrast, for urban customers, who face about one-tenth the average total outage duration as agriculture, the welfare loss from an additional hour per month of outages is equivalent to about a 5.8 percent price increase. These patterns suggest that consumers may not be uniformly better off under an alternative regime in which reliability was higher and prices were raised to cover the additional cost of power purchase. Instead, customers with the lowest value for reliability may prefer to pay lower prices and bear relatively frequent outages.

This paper seeks to contribute to several related literatures. First, it contributes to a growing literature on the political economy and development effects of energy access and regulation in developing countries, including (Mahadevan, 2019; Burlig and Preonas, 2018; Burgess et al., 2020). The analysis here complements McRae (2015)'s study of the infrastructure quality and subsidy trap in Colombia, which uses rich customer-level data to characterize the effects of poor reliability on customer behavior. In contrast, in this paper I use data that is aggregated across relatively large groups of customers but is rich in its temporal resolution and thus enables us to characterize intertemporal responses to outages in the short- and medium-run. In addition, it provides a combination of reduced-form and structural evidence comparing the value of reliability across customer classes to a set of papers each focusing on only one of those classes (Chakravorty et al., 2014; Allcott et al., 2016; Dinkelman, 2011). Finally, the dynamic structural model of electricity demand, which follows dynamic demand models in Hendel and Nevo (2006); Gowrisankaran and Rysman (2012), provides a framework for considering welfare in markets for continuous services or real time markets with no inventories.

The paper is organized as follows: Section 1.2 describes the institutional context in which non-price rationing of electricity arose in India and Maharashtra, as well as the regulatory framework governing electricity distribution by MSEDCL. Section 1.3 characterizes MSEDCL's rationing decisions, presenting analysis of load shedding in response to its costs of wholesale energy procurement. Section 1.4 presents reduced-form estimates of the intertemporal substitutability of electricity consumption in response to load shedding outages across MSEDCL's broad customer categories. Section 1.5 specifies the dynamic structural model of electricity demand under quantity rationing. Section 1.6 describes the estimation procedure, and Section 1.7 presents results.

Figure 1.1: *Load Shedding Outage Frequencies (bars) and Retail Electricity Prices (ranges) in 2017 in MSEDCL, by Customer Category*



The figure shows the load shedding outage frequencies and marginal electricity prices for MSEDCL customers categories in 2017. Customer categories reflect MSEDCL's categorization of distribution feeders. Agriculture feeders serve agricultural pumpsets only, whereas rural and agriculture feeders serve a mix of agriculture, residential, and other services. Average outage probabilities across feeders within these groups are shown in blue bars, corresponding to the lefthand axis. The outage probability is calculated by dividing the number of minutes of outages in 2017 by 525,600, the number of minutes in the year. The minimum and maximum marginal electricity prices across feeders in each category are shown as ranges, corresponding to the righthand axis. Data source: Maharashtra State Electricity Distribution Company Limited; Maharashtra Electricity Regulatory Commission (Maharashtra Electricity Regulatory Commission, 2016).

1.2 Power Outages and Retail Electricity Price Regulation in Maharashtra

1.2.1 Rationing access to electricity in India

In the past two decades, the central challenge to providing universal electricity access in India has evolved from one of mobilizing infrastructure investment to one of regulatory policy. In 2000, about 230 million Indians, 22 percent of the population, were not connected to the electricity grid.[1] Even as demand was constrained by lack of access to the grid, the country faced a peak deficit in electricity generation capacity of about 12 percent, necessitating widespread load shedding across much of the country (The Energy and Resources Institute,

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

2008).[2] Beginning in the late 1990s, India's central government undertook a major regulatory reform program for the electricity sector. This effort was wide ranging, but it principally sought to address underinvestment and resulting capacity constraints in the sector by opening the distribution, transmission, and generation segments to private sector investment and to rationalize retail pricing and service provision by mandating unbundling of vertically-integrated state electricity boards (Pargal and Banerjee, 2014).

Since these reforms, India's power sector has undergone a dramatic expansion. The country's fleet of power plants more than tripled its capacity since 2000, largely erasing persistent deficits in peak capacity that resulted in widespread blackouts in decades past (Central Electricity Authority, 2017). 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 had an electricity connection (Government of India, 2018). These figures suggest that on average about 40 million people per year gained access to the electricity grid during this period.

On the other hand, reforming retail pricing and service provision has proved much more difficult. For decades, India's state power utilities have set retail rates below cost for large segments of their customer bases, particularly agricultural and rural residential customers (Pargal and Banerjee, 2014). Deeply subsidized rates have burdened many utilities with massive debts, contributing to a vicious cycle of underinvestment in grid and generation capacity, poor service quality, and widespread theft and non-payment (Burgess et al., 2020). In 2002, state distribution utilities in India recovered payment for only about 57 percent of the kilowatt hours (kWh) they served to customers due to a combination of line losses, failure to bill customers for energy consumed, and unpaid bills or theft (Power Finance Corporation, 2005).[3] By 2015, recovery had risen to about 72 percent thanks in large part to

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[2]The peak deficit deficit is the difference between the estimated peak electricity load, i.e., the instantaneous demand, and the installed generation capacity.

[3]Average Technical and Commercial Losses reflect the difference between the total energy input in kWh by a distribution utility and the number of kWh on which the utility collected payment.

improved billing and collection by utilities (Power Finance Corporation, 2017). However, the financial position of many utilities worsened during this period. Rapid electrification caused disproportionate growth in consumption by the most subsidized segments of the customer population, while the investment drive in generation has increased the average cost of providing electricity for utilities.

While these reforms largely succeeded in relieving the power system's most acute capacity constraints, quantity rationing remains the dominant allocation paradigm in India's retail electricity markets. Throughout the 20th century, most utilities engaged in a form of long-run quantity rationing. Faced with pressure to keep prices low, utilities rationed access to and investment in the power system. Frequent load shedding under this regime was driven by the resulting physical capacity constraints, primarily in generation, but also to a lesser extent in the transmission and distribution network. The reforms that began in the early 2000s removed control of access and investment decisions from the hands of state utilities, limiting their ability to limit financial losses through this form of long-run rationing. In turn, their costs rose as rural populations grew as a proportion of their customer bases and power plant capacity under contract expanded. Within this new regime, the main way in which state utilities are able to controls costs comes through short-run quantity rationing through rolling blackouts. During the study period of the analysis here, MSEDCL appears to have more power plant capacity under contract than is required to meet peak demand, and yet load shedding remains a daily phenomenon for many customers (Maharashtra Electricity Regulatory Commission, 2016).

1.2.2 Maharashtra Electricity Distribution Company Limited

MSEDCL is India's largest electricity distribution company by number of customers served. Its service territory encompasses a population of about 90 million people, covering the state of Maharashtra except for the city of Mumbai, which has its own distribution system. In 2017, the company served about 25.4 million connections across 41,000 villages and 457 cities and towns. As the end of 2018, MSEDCL's historical peak load was 20,340 megawatts

(MW), about equivalent to that of the Netherlands.

The company was created in 2005 during reforms to the state's electricity system and amid the national drive to improve the efficiency of electricity markets under the Electricity Act, 2003. MSEDCL was one of three companies and a variety of other entities spun out of the former vertically-integrated electricity supply company, the Maharashtra State Electricity Board (MSEB). MSEDCL's mandate is to procure wholesale electricity, operate the low-voltage distribution grid, and connect, meter, bill, and provide customer service to its agricultural, residential, commercial, industrial and government customers. The other two companies spun out of MSEB are responsible for planning, building out, and operating the high-voltage transmission grid (Maharashtra State Electricity Transmission Company, MSETCL) and power plants (Maharashtra State Power Generation Company, MSPGCL), respectively. MSEDCL is regulated by the Maharashtra Electricity Regulatory Commission (MERC). The remainder of this section describes the regulation of wholesale and retail electricity pricing in Maharashtra.

Table 1.1: *MSEDCL Customer Composition by Customer Category, Fiscal Year 2017–2018*

Category	Customers (1)	Energy (2)
Residential	74%	20%
Agriculture	16%	32%
Commercial	7%	7%
Industrial	1%	35%
Other	2%	6%

The table reports the composition of MSEDCL's customer base across four broad categories of customers in terms of the percentage of connections (Customers, column 1) and of total energy consumption (Energy, column 2) in the fiscal year 2017–2018, as reported by MSEDCL to its regulator, MERC. The Other category includes connections to public services and government buildings, as well as temporary connections. Data Source: Maharashtra Electricity Regulatory Commission: MSEDCL Tariff Order 2017-2018

Wholesale procurement

MSEDCL is responsible for procuring sufficient wholesale electricity to serve the consumption, called load, of its customers in each hour. The physics of the electricity grid demand that load and generation equalize nearly instantaneously. In Maharashtra, an independent agency called the Maharashtra State Load Dispatch Centre (MSLDC) is responsible for coordinating the real-time operations of the electricity grid to maintain stability. Along with the distribution companies serving Mumbai, MSEDCL is required to submit day-ahead hourly schedules of its forecasted load (net of the load shedding it plans to undertake) and plant-wise generation to match the forecasted load and then to update these as it approaches real-time. MSLDC then has the authority to dispatch additional capacity or shed load, that is, to implement black-outs, in order to maintain the balance of supply and demand. Both load-serving entities like MSEDCL and power plants are subject to financial penalties for deviating from their scheduled load or generation, respectively.

MSEDCL procures wholesale capacity and energy through a mixture of long-term and short-term contracts with power plants. The overwhelming majority of its capacity and energy comes through long-term bilateral contracts with individual power plants at rates regulated by MERC. There are two types of long-term contracts, reflecting power plant technologies. Dispatchable contracts enable MSEDCL to determine the amount of energy it purchases from each contracted plant in each hour, within the technical limits of the plant, the regulatory guidelines of MERC, and any other contract terms. MSEDCL holds dispatchable contracts with coal- and gas-fired power plants, whose generation can be adjusted up and down relatively quickly in response to fluctuations in demand. For instance, MSEDCL may hold a contract for 200 MW with a coal-fired power plant but only dispatch 100 MW from the plant during off-peak hours. Under non-dispatchable, also called must-run, contracts, MSEDCL is obligated to purchase all of contracted plants' generation up to the total contracted amount when the plant is generating. MSEDCL holds non-dispatchable contracts with nuclear, hydroelectric, solar, and wind power plants.[4]

[4] Several of the hydroelectric power plants with which MSEDCL holds contracts are partially dispatchable.

MSEDCL has no, or very limited, discretion under these contracts about how much or when it purchases wholesale electricity from these plants.

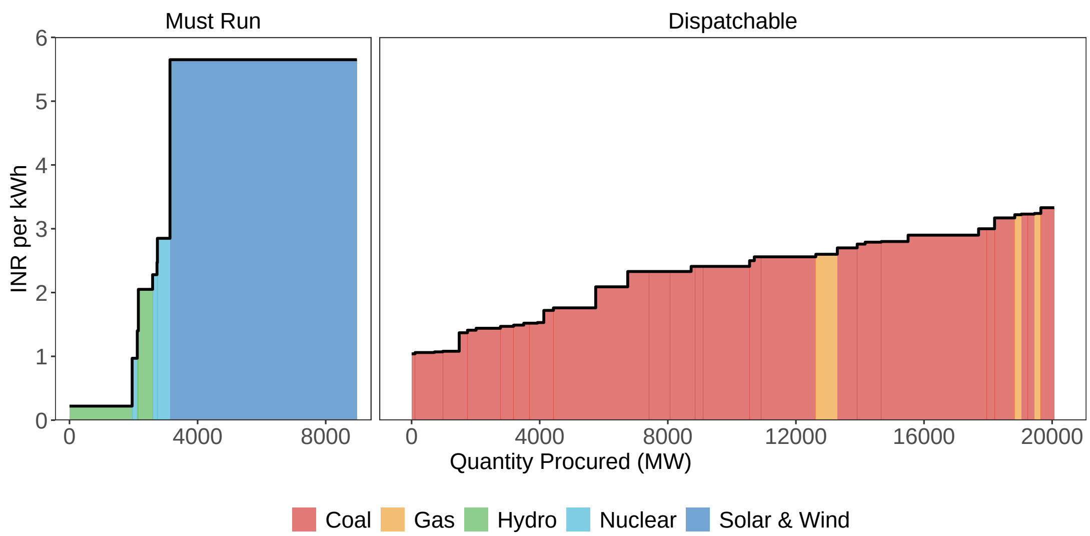
While these contracts are somewhat heterogeneous, all long-term contracts, which are generally 20 or more years in duration, specify available generation capacity in MW and a two-part tariff. Contracts must be approved by MERC, which is frequently involved in negotiating contract terms and disputes. For dispatchable contracts, MERC enforces merit order dispatch, which requires that MSEDCL dispatch plants in increasing order of the variable component of the contract tariff. Figure 1.2 shows an example of MSEDCL's long-term contract network with power plants for January, 2017, in merit order and colored by generation technology. The right panel shows dispatchable contracts with coal- and gas-fired power plants, and the left panel shows non-dispatchable must-run contracts with nuclear, hydroelectric, and wind and solar power plants.

Retail pricing

As with wholesale contract rates, retail electricity prices are regulated by MERC. Retail prices vary dramatically across customer categories, and the tariff structure is complex. In general, customers pay a fixed charge that is proportional to the size, measured in kilowatts (KW), of their connected load and a variable component per kWh each billing cycle. Figure 1.3 presents a simplified illustration of the marginal component of the tariff structure by customer category during the first half of 2017. Because marginal rates may depend on other attributes of the customer's connection, like its voltage for commercial and industrial customers, this plot presents the median rate for each category. At about 1 INR (1.4 cents USD) per kWh, prices are lowest for residential customers registered as below poverty line. These customers can consume up to 100 kWh per billing cycle at this rate. For the agricultural customers that are metered, the rate was about 3 INR (4.2 cents USD) per kWh, while the approximately 50 percent of agricultural customers that are unmetered pay

These dammed hydroelectric plants are able to follow load when they have sufficient water levels, which is seasonal. During these periods, MSEDCL may coordinate with the dam operators to dispatch these plants at peak times in order to reduce the costs of its dispatchable energy requirements.

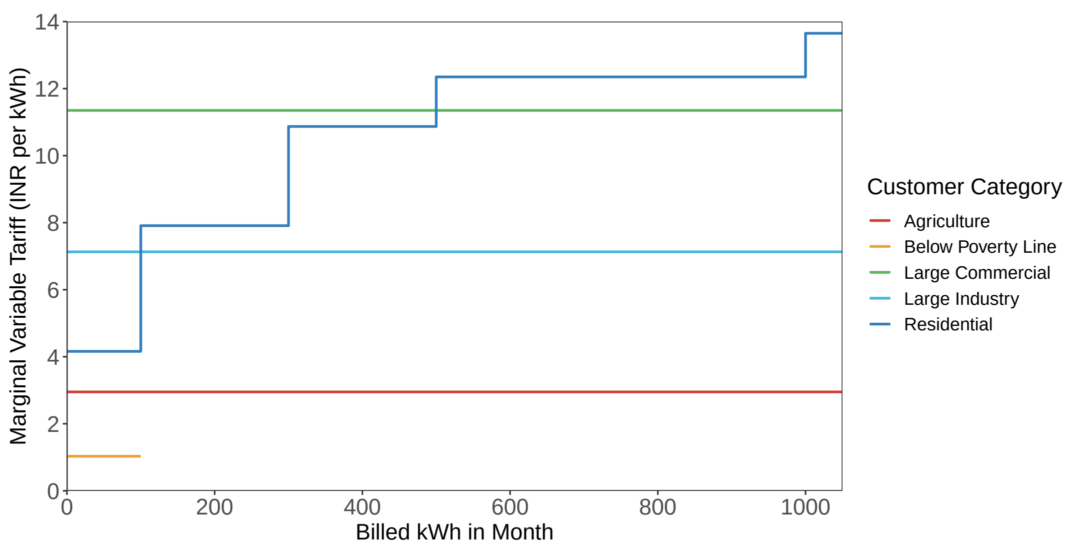
Figure 1.2: *MSEDCL Wholesale Power Purchase Cost by Technology, January 2017*



The figure shows MERC-approved energy purchase contracts held by MSEDCL in January 2017, arranged in order of increasing variable cost (merit order) and shaded by generator technology. The left panel shows must-run contracts with non-dispatchable power plants, and the right panel shows contracts with dispatchable power plants. Each step corresponds to one or more contracts at each level of variable cost (vertical axis). The length of the step corresponds to the quantity in MW available under each contract or contracts. Data Source: Maharashtra Electricity Regulatory Commission: MSEDCL Tariff Order 2017-2018 no marginal price. Residential customers are subject to an increasing block tariff, although about 85 percent of these customers were on the bottom step. Industrial and commercial customers paid the highest marginal rates, at about INR 7 (9.8 cents USD) and INR 11.5 (16 cents USD) per kWh.

MSEDCL's average variable cost of wholesale electricity procurement during this period is almost exactly equal to the bottom step of the residential block tariff, at just above 4 INR (5.6 cents USD) per kWh. On variable costs, MSEDCL approximately breaks even on residential customers on this bottom step, while it loses money on average on below poverty line and agricultural customers. Commercial and industrial customers effectively pay a substantial cross-subsidy to these other groups.

Figure 1.3: *Median Marginal Component of MSEDCL Electricity Price by Customer Category, 2017*



The figure shows a simplified representation of the marginal component of the MSEDCL retail tariff schedule for 2017 by customer categories. The horizontal axis is the quantity in kWh consumed by a customer in a billing cycle. The vertical axis is the price per kWh of the *last* unit of consumption. The dashed gray line shows the average variable cost of MSEDCL, as reported to its regulator, MERC. Data Source: Maharashtra Electricity Regulatory Commission: MSEDCL Tariff Order 2017-2018

1.3 Load Shedding Responses to Wholesale Costs

This section develops an empirical test of the hypothesis that MSEDCL uses load shedding as a means of quantity rationing. Regulations governing MSEDCL prohibit from load shedding except in the event of capacity constraints. As the main regulatory document covering MSEDCL's operations during the study period states, "[t]he load shedding protocol was devised as a load regulation measure to address significant power shortage situation then prevalent in the State [prior to 2016]. In case there is sufficient availability of power, no consumer should be subjected to load shedding" (Maharashtra Electricity Regulatory Commission, 2016). MSEDCL there acknowledges that there is sufficient availability of power under contract. However, throughout 2017 and 2018, load shedding was common. In a average hour during this period, about two percent of MSEDCL's power lines serving customers were under a load shedding outage. Moreover, load shedding is not heavily concentrated at peak times of the year and day when capacity constraints are mostly likely to bind. Appendix Figures A.1 and A.2 show the the monthly and hourly patterns of load shedding and total load served by MSEDCL. As illustrated in Figure 1.1, the frequency of load shedding outages on individual power lines was strongly correlated with the types of customers served by those lines, with the most subsidized customers seeing the most frequent blackouts.

To characterize MSEDCL's rationing behavior, I estimate the responsiveness of the utility's hourly load shedding to its costs of wholesale energy procurement using an instrumental variables strategy. MSEDCL's wholesale procurement costs are not observable hourly, but the contract network and the state's regulation of power plant dispatch enable me to construct MSEDCL's variable cost curve for each month of 2017 and 2018. I then incorporate hourly data on maintenance and unanticipated technical breakdowns at power plants under contract to MSEDCL contract the cost curve for each hour. Appendix A.1 provides a detailed description of the procedure used for estimating the hourly cost curves. To isolate the effect of variation in MSEDCL's marginal cost of power procurement on its load shedding decisions, I use non-dispatchable generation from contracted wind power plants as an instrumental variable (IV). The analysis shows that MSEDCL's load curtailment decisions are highly responsive to its pricing incentives: in response a one standard deviation increase in the marginal cost of wholesale electricity, on average MSEDCL shed load to distribution feeders serving about 246,000 people.

1.3.1 Empirical strategy

A variety of factors aside from cost control could explain the correlation between forced power outages and wholesale costs. Most importantly, load shedding and wholesale costs are simultaneously determined. MSEDCL's load shedding decision is equivalent to choosing the quantity it supplies in any given hour. Forced to dispatch contracted power plants in increasing order of the variable component of the contracted tariff, shedding more load will weakly reduce the variable component of the tariff paid to the marginal generator. Moreover, load shedding conducted in anticipation of insufficient network capacity is also likely to be correlated with wholesale costs through demand shocks. Each piece of infrastructure in the transmission and distribution network has a maximum capacity, and therefore increased load shedding could be explained in part by insufficient network capacity during peak demand. In addition, certain types of distribution network equipment failures may be more likely during hot weather when demand peaks, causing distribution utilities to shed load as a preventative measure.

The analogy to demand estimation motivates the identification strategy, which employs a cost-shifting IV. I use wind generation conditional on a rich set of fixed effects to generate plausibly exogenous variation in the variable contract cost of the marginal generator in MSEDCL's cost curve. As in demand estimation, must-run wind generation acts a supply shifter, causing variation in the cost of MSEDCL of serving any given level of load. Figure 1.4 illustrates the approach for a particular hour. The red curve shows the variable cost of each dispatchable generator under contract to MSEDCL in merit order for the hour ending 6 PM on May 1, 2018. The orange curve shows the same cost curve, but adds to it the approximately 1,500 MW of must-run generation MSEDCL received in this hour from wind generators with which it holds contracts. The dotted line shows the load MSEDCL served in this hour, approximately 15,000 MW. The intersection of the dotted line with the black and red cost curves reflects the effect of receiving non-dispatchable generation from wind on the marginal cost of wholesale electricity for MSEDCL: had there been no wind generation in this hour, the cost of serving the same level of load would have been higher by more than 10 percent.

The first stage estimating equation is

$$MC_{d,h} = \alpha Wind_{d,h} + \beta X_{d,h} + \gamma_d + \gamma_h + \epsilon_{d,h}, \tag{1.1}$$

where $MC_{d,h}$ is the contracted variable cost of the generator at the margin on day d in hour h, $Wind_{d,h}$ is the generation by wind power plants received by MSEDCL, $X_{d,h}$ is a set of date-hour controls, including the total load served in MSEDCL and the neighboring utility in Mumbai, transmission congestion, and weather, and γ_d and γ_h are date and hour fixed effects, respectively. Mumbai's distribution utilities have among the highest levels of reliability of Indian utilities. I include the load served in Mumbai as a control to proxy for demand shocks that may be censored by rationing. An index for congestion in the interstate transmission network is constructed based on the deviation in regional 15-minute market clearing prices in India's wholesale electricity spot market.[5] The results reported below are robust to the exclusion of any or all of these controls.

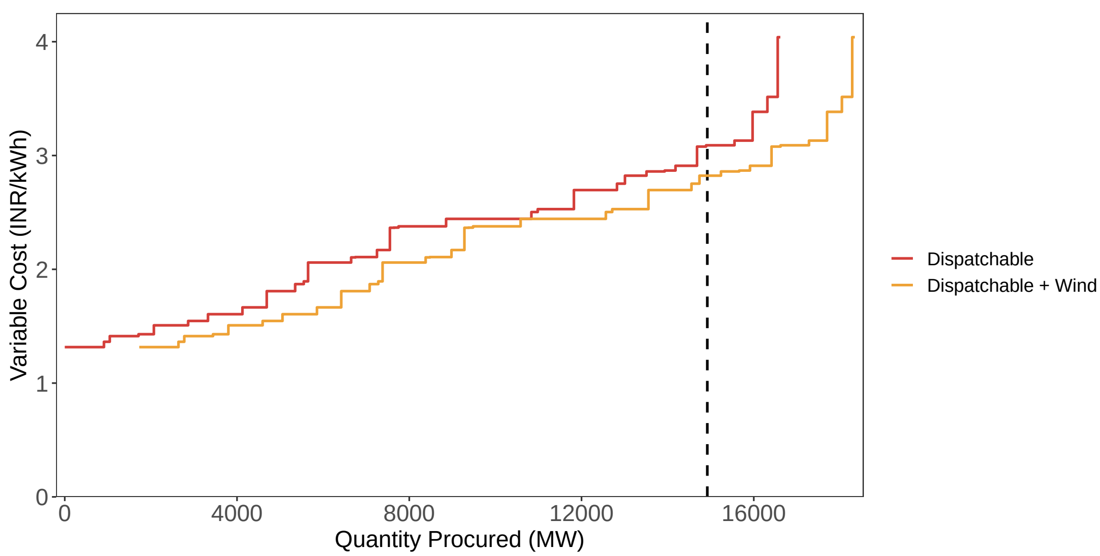
The second stage regresses the number of feeders facing load shedding in hour h on date d, $Out_{d,h}$, on the predicted marginal cost from the first stage, $\hat{MC}_{d,h}$:

$$Out_{d,h} = \theta \hat{MC}_{d,h} + \delta X_{d,h} + \gamma_d + \gamma_h + \omega_{d,h}. \tag{1.2}$$

[5] India has two national day-ahead bid-in wholesale electricity markets. These markets clear in 15-minute blocks for 13 regions of India. When the transmission network is unconstrained nationwide, the 15-minute prices for the regions are all equal. However, prices diverge when transmission constraints prevent profitable trades. The index of transmission constraints used here is the market clearing price for the West 2 Region of Indian Energy Exchange, which covers MSEDCL, minus the mean across the 12 other regions over the West 2 price. When there is no congestion, the value of the index is 0. When the index is positive, the market clearing price is higher in West 2 than elsewhere, indicating a relative shortage of capacity in West. When the index is negative, the market clearing price in West 2 is lower than elsewhere, indicating a relative surplus.

The exclusion restriction requires that, conditional on controls and date and hour of day fixed effects, wind generation is uncorrelated with the residual determinants of demand. Given that I condition on wind speed and a host of other weather variables affecting the service territory of MSEDCL, the variation in the instrument that identifies the effect likely comes from localized wind patterns near the turbines. Appendix Figures A.1 and A.2 show the hourly and seasonal patterns of wind generation alongside those of the other main variables. In the median hour, wind generation comprises about 3 percent of purchased energy, reaching its peak in July during the monsoon.

Figure 1.4: *Variable Cost of Electricity Supply for Maharashtra Electricity Distribution Company Limited (MSEDCL), Hour Ending 6 pm on May 1, 2018*



The figure illustrates variation in marginal wholesale costs of electricity facing MSEDCL generated by non-dispatchable wind generation contracts. The black line shows the dispatchable energy purchase contracts held by MSEDCL in the hour ending 6 pm on May 1, 2018, arranged in order of increasing variable cost (merit order). Each step corresponds to one or more contracts at each level of variable cost (vertical axis). The length of the step corresponds to the quantity in MW available under each contract or contracts. The red line adds to the black line the receipt of generation from non-dispatchable energy purchase obligations with wind generators. The dashed vertical line corresponds to the total load in MW served in the hour. Data Source: Maharashtra State Load Dispatch Centre.

1.3.2 Data

Load shedding power outages. I observe load shedding power outages at the distribution feeder level for 2017 and 2018. Records of the timing of about 1.4 million load shedding outages during this period were collected from the MSEDCL website.[6]

Wholesale electricity procurement costs. The model of power plant dispatch relies on monthly contract-level data, prices from the wholesale spot market, and hourly power-plant level operation data. Each of the wholesale electricity contracts between MSEDCL and its suppliers are documented extensively in MERC documents. However, these contracts frequently change over time. For example, many of the contracts have components that are indexed monthly to coal prices, allowing power plants to pass through a portion of fuel price changes to MSEDCL. As a result, the variable component of many contracts are time varying. The MSLDC, which implements merit order dispatch, publishes updates to contract prices for each power plant.[7] I construct a time series of each contract's variable cost component for 2017 and 2018. For less than 10 percent of hours, MSEDCL also procures electricity from the day-ahead wholesale spot market or through bilateral contracts with other distribution utilities, particularly those serving Mumbai. While the rates for bilateral contracts are generally not available, I collect market clearing prices from the India Energy Exchange in order to account for spot market purchases in the dispatch model.[8]https://www.iexindia.com/marketdata/areaprice.aspx . Finally, I collect data on generator downtime due to maintenance, breakdowns, and fuel shortages from the Daily System Report of the MSLDC.[9]https://mahasldc.in/home.php/daily-reports/.

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[6]Feeder-level outage data are available on MSEDCL's website: https://consumerinfo.mahadiscom.in/feeder/feeder_outage.php.

[7]Monthly merit order dispatch stack reports are available from MSLDC's website: https://mahasldc.in/home.php/monthly-mod-stack/.

[8]Market clearing prices by region were scraped from the India Energy Exchange's website: https://www.iexindia.com/marketdata/areaprice.aspx

[9]Daily System Report available from MSEDCL's website: https://mahasldc.in/home.php/daily-reports/

Weather. The analysis also controls for 6-hour temperature, precipitable water, relative humidity, atmospheric pressure, wind speed and direction for MSEDCL's service territory using the NCAR/NCEP Reanalysis I dataset (Kalnay et al., 1996).

Table 1.2 reports summary statistics for the main variables used in the empirical analysis.

Table 1.2: *Summary Statistics: Load Shedding and Power Purchase Costs*

	Mean	Std. Dev.	25%	50%	75%	95%	Max.
Feeders Under Outage in Hour	372.5	207.9	246.9	363.0	493.0	668.5	2174.3
Marginal Cost (INR/kWh)	3.20	0.78	2.73	3.02	3.47	4.70	11.3
Wind Generation (GW)	0.76	0.72	0.21	0.47	1.09	2.32	3.16
MSEDCL Load Served (GW)	15.7	1.96	14.1	15.7	17.3	18.8	20.7
Mumbai Load Served (GW)	2.45	0.50	2.08	2.45	2.85	3.26	3.67
Congestion Index	-0.013	0.048	0	0	0	0.0019	0.25
Observations	16144						

The table presents summary statistics for the dataset used to estimate the regressions described in equations (1.1) and (1.2). The Congestion Index is calculated as the average Indian Energy Exchange West 2 regional 15-minute minus the mean across the 12 other regions over the West 2 price. When there is no congestion, the value of the index is 0.

1.3.3 Results

Table 1.3 reports the results of the IV regressions described in equations (1.1) and (1.2) for 16,144 hours during 2017 and 2018. The controls include 6-hour weather parameters described above, the load served in MW by MSEDCL and one of Mumbai's utilities, and the index for transmission congestion. The first two columns report the OLS results with and without these controls. In both specifications, feeder outages are strongly positively correlated with the marginal cost of procuring power, reflecting MSEDCL's upward sloping cost curve. The first stage is shown in column 3: when MSEDCL received an additional 1,000 MW of wind generation, its marginal cost falls by about .21 INR (.29 cents USD) per kWh, or about 6.5 percent of the mean marginal cost. The instrument is quite strong, with an *F* statistic of 179.6. In column 2, the second stage shows that MSEDCL shed about 82 additional feeders in response to a one INR (1.4 cents USD) per kWh increase in the marginal cost of wholesale electricity procurement in 2017 and 2018. In the average hour during this period, about 180 MSEDCL's 16,000 feeders faced load shedding. Based on a rough calculation of the average population served by each distribution feeder, the estimated effect translates to about an additional 246,000 people facing power outages as a result of a one standard deviation increase in the marginal cost of wholesale electricity to MSEDCL. These results support the conclusion that MSEDCL uses load shedding to control variable costs.

Table 1.3: *Feeder Load Shedding Outages on MSEDCL Marginal Cost, Instrumented with Wind Generation*

	OLS		IV	
			First Stage	**2SLS**
	Feeder Outages	Feeder Outages	Marginal Cost	Feeder Outages
	(1)	(2)	(3)	(4)
Wind Generation (GW)			-0.209***	
			(0.0156)	
Marginal Cost (INR/kWh)	59.45***	15.89***		82.07***
	(2.447)	(1.612)		(15.83)
MSEDCL Load Served (GW)		-31.44***	0.227***	-46.70***
		(1.047)	(0.00487)	(3.793)
Mumbai Load Served (GW)		110.3***	0.0468**	107.5***
		(4.426)	(0.0220)	(4.709)
Congestion Index		83.08***	0.448***	54.62***
		(17.33)	(0.0860)	(19.47)
Weather Controls		✓	✓	✓
YMD FEs		✓	✓	✓
Hour FEs		✓	✓	✓
Mean of Outcome	372.5	372.5	3.203	372.5
Observations	16144	16144	16144	16144
First Stage F				179.6
R^2	0.0498	0.861	0.756	

The table presents results of the 2SLS regressions described in equations (1.1) and (1.2). Column one reports the first stage, which regresses the marginal cost of wholesale electricity in the hour on the wind generation received in the hour and controls. Column two reports the second stage, which regresses the number of feeders facing load shedding outages in the hour on the predicted marginal cost from the first stage and controls. The controls include: an index of transmission congestion constructed from the differences in regional market clearing prices in the day-ahead wholesale spot market of the India Energy Exchange; 6-hour temperature, precipitable water, relative humidity, atmospheric pressure, wind speed, and wind direction; MSEDCL total load served; and the total load served in the hour by Tata Power Corporation Limited in Mumbai. * $p < .1$, ** $p < .05$, *** $p < .01$

1.4 Intertemporal Substitution Responses to Load Shedding

In order to evaluate the cost to consumers from the rationing regime characterized in the previous section, the model of dynamic electricity demand under power outages that is developed in the next section represents the welfare loss from a power outage as a constraint away from consumers' optimal path of consumption through time. It posits that the magnitude of the welfare loss is greater for consumers who are less able to substitute consumption lost to outages to other periods of time. In this section I seek to analyze descriptively how consumers respond to power outages using hourly consumption observations aggregated at the feeder level. Aside from the composition of customer types served by each feeder, few details are available about the individual customers who comprise these feeders. However, millions of hourly load observations enable a detailed analysis of intertemporal substitution patterns across MSEDCL's customer categories. This analysis shows that the customer categories that are both most heavily subsidized and most severely rationed have the highest degree of intertemporal substitutability in demand in the short run. In particular, agricultural consumers lose less than half an hour's average consumption in response to an hour of power outages, while commercial and industrial consumers lose nearly twice an hour's average consumption in response to an hour of outages.

1.4.1 Empirical strategy

The analysis here seeks to estimate the causal effect of power outages on power line level electricity consumption in adjacent hours in order to analyze the short-run intertemporal substitutability of electricity consumption across MSEDCL's customer categories. The central causal identification challenge arises from the correlation between the timing of power outages and potentially unobservable determinants of electricity demand discussed in the previous section. Regressions of consumption on outages in adjacent periods suffer from omitted variable bias due to the selection introduced by the rationing process. The importance of this selection is illustrated in the fact that feeders generally see more electricity consumption on days when they face load shedding than on days when they do not, in spite of the mechanical reduction in consumption introduced by these outages. In analysis at both the day and hour level, the identification strategy relies on power line and time fixed effects along with flexible controls for weather and patterns of past outages outside the time window of interest.

Across various specifications at the daily and hourly levels, the main estimation equations take the form:

$$y_{m,t} = O'_{m,t}\alpha + g(X) + \gamma_m + \gamma_t + \epsilon_{m,t}, \tag{1.3}$$

where $y_{m,t}$ is log electricity consumption, referred to as load, on distribution feeder line m in time period t; $g(X)$ is a function of demand determinants, X, which is itself a vector; γ_m and γ_t reference feeder and time period fixed effects, respectively, and $\epsilon_{m,t}$ is an error. In daily specifications, t indexes dates and $O_{m,t} = o_{m,t}$ is the total duration of power outages on the feeder. In hourly specifications, t indexes date-hours and $O_{m,t}$ is a vector of outage durations realized in lagged hours.

Two-way fixed effects draw their appeal as an identification strategy from the institutional details of load shedding by MSEDCL. As the evidence the previous section showed, the timing of load shedding in Maharashtra is driven by aggregate supply and demand conditions.[10] On the other hand, the targeting of load shedding across the approximately 16,000 feeder lines in MSEDCL's network is driven primarily by the composition of customers served by each line. In particular, lines serving more heavily subsidized feeders experience dramatically more frequent load shedding. While the exact mix of customers served by each line evolves over time, MSEDCL groups lines into about 60 types based on their composition. During the study period, very few lines change type. Moreover, it is very difficult to monitor and target load shedding to individual feeders, and therefore it is

[10]In the presence of transmission constraints, load shedding decisions could be driven by regional, rather than aggregate, market conditions. For example, lack of sufficient generation capacity or high contracted cost of local generators could prompt a utility to conduct load shedding in one sector of its service territory in response to localized supply or demand shocks. In MSEDCL's case, there is little evidence that transmission constraints drive load shedding decisions. In the main regulatory order for the period under study documenting detailed oversight inquiries by the Maharashtra Electricity Regulatory Commission and responses from MSEDCL, a document that runs 617 pages, there is no mention of transmission constraints in association with load shedding (Maharashtra Electricity Regulatory Commission, 2016).

unlikely that MSEDCL is able to target load shedding in response to feeder-specific demand shocks.

The fixed effects strategy is consistent with a simple model of rationing in which each feeder is assigned a predetermined, time-invariant priority ranking and then the total number of feeders shed in each hour is determined by aggregate market conditions. Rolling blackouts can be captured in this model with ranking ties broken by a randomization. This model lends itself to a difference-in-differences conditional independence assumption in which, conditional on a feeder's ranking (γ_m) and aggregate demand conditions (γ_t), outages are a good as randomly assigned. Historically many state utilities, including MSEDCL, have published rationing priority rankings that group feeders and, in some cases, even indicate hours during which feeders of particular categories may face load shedding (Harish and Tongia, 2014; Maharashtra Electricity Regulatory Commission, 2016).

While two-way fixed effects capture the basic assignment mechanism plausibly operating under load shedding, successions of rolling blackouts introduce an additional complication for identification. Depending on the time horizon considered, load shedding outages on an individual power line may be positively or negatively serially correlated. Feeders that are very low in the priority order and are shed first are likely to experience spells during which outages occur every day for a series of days during which during which the wholesale market is constrained, for example, due to weather conditions or generator failures. In contrast, if MSEDCL conducts rolling blackouts, then experiencing an outage today may reduce the probability of experiencing an outage tomorrow, all else equal. In either case, past outages may translate into non-parallel demand shocks across similar feeders compared in a differences-in-differences strategy. An alternative way to interpret potential serial correlation in outages is in terms of anticipation of outages by consumers (Joskow and Tirole, 2007). If customers learn patterns of outages based on past experience, then they may reshape their consumption in response. To the extent that their beliefs about outage probabilities are correlated with realizations, these anticipation effects will generate bias in the difference-in-differences approach without adequate conditioning. In the example of rolling blackouts, lower levels of planned consumption on days with more outages will result in an underestimation of the intertemporal substitutability of electricity consumption. The strategy here attempts to flexibly control for each feeder's past realizations of outages, including the hours over outages over recent days, and hourly outage frequencies over the past two months.

The possibility that consumption responds to outages realized outside of the window of analysis, that is, within the same day or in the past 24 hours, motivates the approach to control for past outages and weather nonparametrically in $g(X)$. To do so, I follow Chernozhukov et al. (2018), allowing a random forest to fit regression functions of contemporaneous consumption, $y_{m,t}$, on past outages and weather and contemporaneous outages, O, on past outages and weather. I refer to these two regression functions as auxiliary. X is comprised of 92 controls: 6-hour weather conditions from the Kalnay et al. (1996) dataset used in the analysis of load shedding above (precipitable water, relative humidity, temperature, wind speed and direction), 14 lags of daily total hours of outages experienced, three lags of monthly hour-specific outage frequencies. Random forest is well-suited to fitting the auxiliary regression functions or two main reasons. First, it captures potentially complex, high-order interactions without requiring specification of these terms. These interactions are likely to be important given the potential complexity of rolling blackouts and consumers' process of learning about outage probabilities. For example, outages on three successive days may to inform a fairly accurate and precise prediction about the likelihood of an outage on the fourth day. Second, in contrast, many of the included controls are likely to be irrelevant, and the random forest's explanatory variable selection algorithm effectively accommodates many poorly predictive regressors without imposing a curse of dimensionality (Breiman, 2001; Athey and Imbens, 2019).

The Chernozhukov et al. (2018) procedure follows the logic of residual regression. The random forest is used to fit the auxiliary regression functions in order to compute the residuals:

$$\tilde{y}_{m,t} = y_{m,t} - \hat{y}_{m,t} \tag{1.4}$$

and

$$\tilde{O} = \tilde{o}_{m,t} = o_{m,t} - \hat{o}_{m,t}, \tag{1.5}$$

where $\hat{y}_{m,t}$ and $\hat{o}_{m,t}$ are predicted values from separate random forest fits on X for the daily specifications. In the hourly specifications, O is a vector and each component is residualized on X using a separate random forest fit:

$$\tilde{O} = \begin{pmatrix} \tilde{o}_{m,t,1} = o_{m,t,1} - \hat{o}_{m,t,1} \\ \vdots \\ \tilde{o}_{m,t,\tau} = o_{m,t,\tau} - \hat{o}_{m,t,\tau} \end{pmatrix}, \tag{1.6}$$

where τ is the length of O. Finally, OLS is used to estimate the average treatment effects:

$$\hat{\alpha} = \left(\tilde{O}'\tilde{O}\right)^{-1} \tilde{O}'\tilde{y}_{m,t} \tag{1.7}$$

I augment this procedure by adding two-way fixed effects. Because I consider the fixed effects critical to the identification strategy, I partial out the fixed effects prior to fitting the auxiliary functions.

The consistency of this approach depends on sample splitting. The "cross-fitting" procedure proposed in Chernozhukov et al. (2018) partitions the sample into two or more subsamples, fits the random forest using the subsamples, but generates the predicted values $\hat{y}_{m,t}$ and $\hat{O}$ using data held out from the subsample. It then averages the estimated predicted values across the alternative models from the subsamples. The hyperparameters of the random forest that govern the number and depth of the trees are themselves chosen by 10-fold cross validation. In general, the results a very robust to alternative tuning parameters.

The main threat to identification under this strategy arises from targeting of load shedding on the basis of regionally-idiosyncratic demand shocks not driven by weather. For example, slight differences in the timing of agricultural activities may affect watering schedules and hence agricultural demand, which is overwhelmingly irrigation pumpsets. As a consequence of conditioning on past outage realizations, the strategy here isolates unexpected outages. However, depending on the time horizon over which these adjustment occurs, the welfare losses from persistent but modest distortions in consumption patterns due to anticipation of outages may be substantial relative to the large but short-lived distortions in response to an unexpected outage realization. By specifying the form of consumers' expectations, the model enables me to separate these two effects and consider the welfare costs associated with each.

In order to compare responses to outages across customer categories, I estimate substitution effects separately for agriculture, rural mixed agriculture and residential, rural residential, urban, and commercial and industrial feeder lines separately. While the dataset of hourly outages and feeder-level consumption comprises about 50 million observations, outages occur relatively infrequently and their frequencies vary across these customer categories. The random forest strategy employed here has the benefit of provides a data-driven approach to the inclusion and flexibility of regressors in X on the basis of the strength of the signal in outages realizations and these demand determinants for each customer category.

1.4.2 Data

In addition to the feeder-level outage and weather data described above, this analysis uses hourly feeder-level electricity consumption data for 2017 and 2018. I collected hourly feeder-level electricity consumption data for the universe of non-government customers on 16,633 feeders from the MSEDCL website for 2017 and 2018.[11]https://www.mahadiscom.in/hourly-feeder-load-information/. On average, the coverage of this dataset is about 50 percent of the hours during these two years, totaling more than 140 million observations. Feeders are categorize in 96 categories according to the characteristics of the customers connected to each line, and I group these into five broad categories for the purposes of analysis. These categories are: agriculture; rural mixed, feeders serving a mix of rural residential and agricultural customers; rural residential-only feeders; urban feeders, comprising a mix of residential commercial and small industry; and commercial and industrial (C&I), comprising

[11]MSEDCL hourly feeder load data are available in pdfs on the MSEDCL website: https://www.mahadiscom.in/hourly-feeder-load-information/

large consumers that generally take electricity at higher voltages.

1.4.3 Results

Daily

Regressions at the feeder-day level summarize the extent of substitution in response to outages within the same calendar day across the five customer categories. Table 1.4 presents the results of the daily specification, showing OLS results in the top panel and the Chernozhukov et al. (2018) estimation procedure in the lower panel. The unconditional OLS results reflect both substitution and the selection process resulting from the rationing mechanism. Feeders comprised of agricultural customers (columns 1 and 2) see about 3.1 percent more load for each hour of outage, whereas feeders comprised of a mix of agricultural and rural residential customers (columns 3 and 4), only rural residential (columns 5 and 6), urban mixed residential and commercial (column 7 and 8), and large commercial and industrial customers (columns 9 and 10) all see reductions in load with more outages. Once the fixed effects, weather, and past outage controls are included, many of these relationships reverse though without a clear interpretation. To put these magnitudes into context, one hour is about 4.2 percent of a day.

The results from the orthogonalized random forest procedure in the bottom panel present a more coherent picture. The effects for agriculture and rural mixed feeders are small, negative, and insignificant, while the effects are larger in magnitude and significant for the other three categories. The effect is largest for commercial and industrial customers, which reduce their consumption by 6.8 percent for each hour of outage. Rural residential and urban consumers see reductions of 2.7 percent and 1.7 percent per hour of outage, respectively. It is important to note that these specifications make it difficult to disentangle the substitution response from the correlation between each customer category's within-day load pattern and outage probabilities. This relationship is strongest for agricultural customers, whose demand peaks midday along with load shedding. On the other hand, commercial and industrial customers have very flat intraday load patterns. With this consideration in mind, the comparison of these effects may understate the degree of variation in the intertemporal substitutability of consumption across the categories. Another caveat is that substitution responses may propagate into the next day, particularly if they happen later in the day.

While these estimates are limited in the ways described above, they offer useful insight on the magnitude of the short-run welfare implications of rationing for each customer category. If consumption is close to perfectly substitutable through the day in response to an outage, then these effects might be expected to be close to zero as long as the power is on for some portion of the day and prices do not vary within the day.[12] This appears to be approximately the case for agricultural customers. At the other extreme, if there is complementarity in consumption through the day, then the magnitude of consumption lost may be very large. Commercial and industrial customers, which see about 1.6 times an average hour's consumption lost for each hour of outage may be closer to this extreme.

Hourly

Figure 1.5 presents the results of hourly regressions estimated using the orthogonal random forest procedure graphically, decomposing the effects presented in the daily regressions to show the time path of consumption responses to outages. Here O' is a vector of 24 indicators for an outage in each of the 24 lagged hours. These specifications include feeder, date, and hour of day fixed effects, and thus also address the limitation related to variation in within-day demand and outage patterns. The figures plot the coefficients and 95 percent confidence intervals for the coefficients on the 24 lagged effects. The figures show the coefficients mirrored across the vertical axis so as to show the shape of the consumption response to an outage over the following 24 hours. The effect at 1 on the horizontal axis reflects the coefficient on lag 1 hour, the effect at 2 on lag 2 hours, and so on. The vertical axes are standardized to facilitate comparison across the categories.

Agricultural consumers increase consumption by up to 8 percent in the 18 hours follow-

[12] A small portion of large commercial and industrial customers are exposed to time of day pricing, which varies the price through the day according to a predetermined schedule (Maharashtra Electricity Regulatory Commission, 2016).

ing an outage. Near the end of the window, these effects are slightly negative. Commercial and industrial customers show the least substitutability, seeing reductions in consumption over the eight hours following an outage. Rural mixed, residential, and urban customers show relatively modest but sustained increases in consumption in the 8 to 24 hours following an outage.

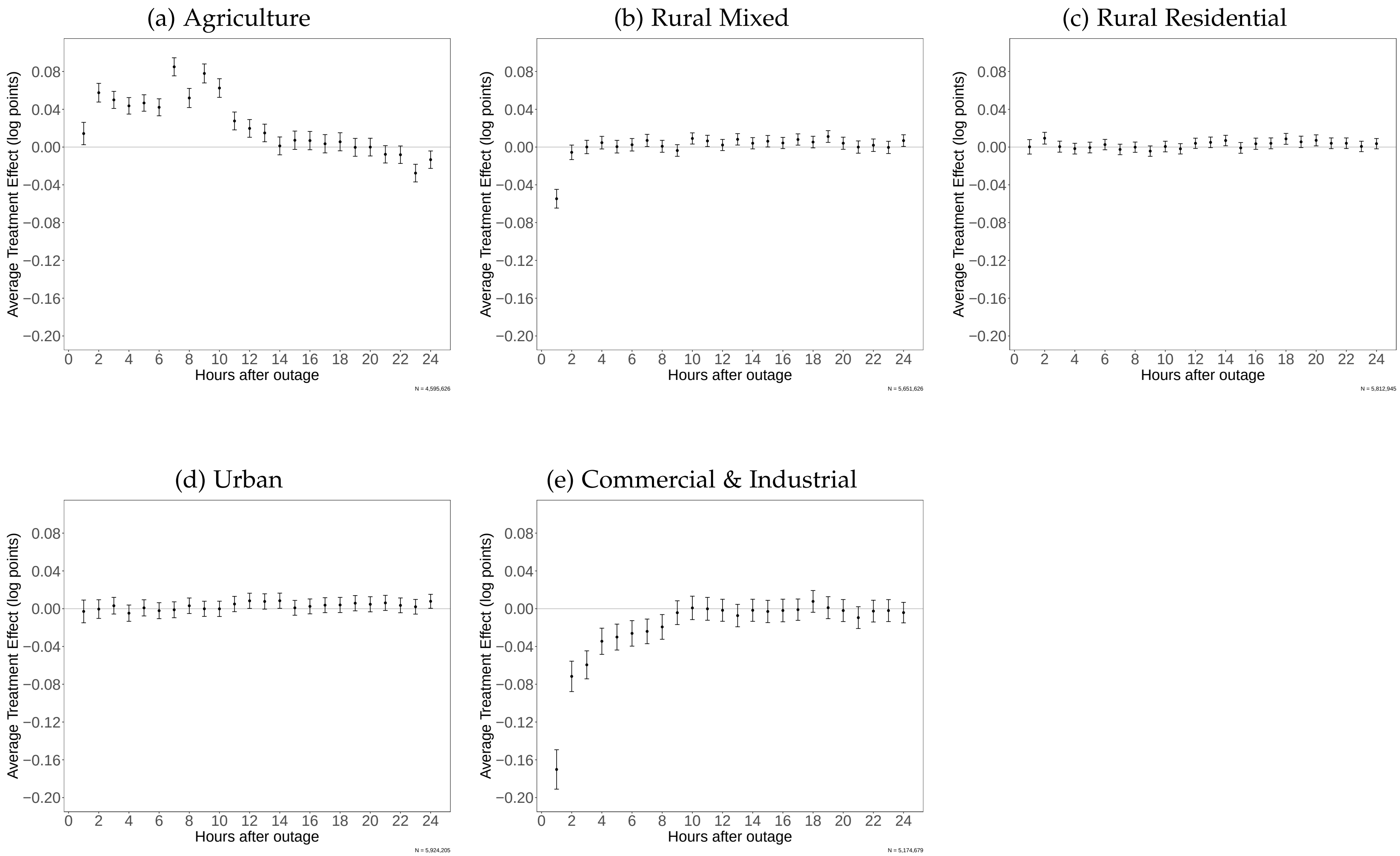
Table 1.4: *log Daily Feeder Load on Hours of Outage, 2017 to 2018*

	Agriculture		Rural Mixed		Rural Residential		Urban		Commercial & Industrial	
A. OLS										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hours of Outage	0.03045***	-0.003539	-0.01649***	0.1075***	-0.005429	-0.05527***	-0.002788	0.001538	-0.05594***	0.1906***
	-0.00233	-0.004204	-0.006188	-0.01421	-0.003485	-0.008113	-0.004249	-0.01198	-0.008091	-0.02277
YMD FEs		✓		✓		✓		✓		✓
Feeder FEs		✓		✓		✓		✓		✓
HD Controls		✓		✓		✓		✓		✓
Observations	947,382	947,382	147,992	147,992	326,541	326,541	423,001	423,001	276,479	276,479
Feeders	6,608	6,608	1,016	1,016	2,150	2,150	2,852	2,852	2,022	2,022

B. DML	(1)	(2)	(3)	(4)	(5)
Hours of Outage	-0.001776	-0.008516	-0.02659***	-0.01721***	-0.06593***
	-0.002259	-0.006205	-0.003485	-0.004355	-0.007182
Observations	947,382	147,992	326,541	423,001	276,479
Feeders	6,608	1,016	2,150	2,852	2,022

The table report results from the regressions described in Section 1.4. The top panel reports OLS results. HD Controls refers to 92 weather and past outage controls. The bottom panel reports results from the orthogonalized random forest procedure. * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 1.5: *Treatment Effects: Electricity Consumption on Past Outages by Customer Category, 2017–2018*



The figures plot the estimated coefficients and 95 percent confidence intervals for lagged hours of outage described in section 1.4.1. The estimation procedure is conducted separately for a sample of 1,000 feeders from each customer category.

1.5 Model: Dynamic demand for electricity with outages

This section describes a dynamic model of electricity demand under non-price rationing and time-invariant prices for a single retail consumer. The consumer is forward-looking over a finite horizon of hours, and she has beliefs about the probability of a power outage in each of the hours within the horizon. In each hour she chooses a level of electricity consumption. The marginal utility of electricity consumption in the hour depends on demand conditions, including the hour of the day, month of the year, and the weather, as well as on usage – and therefore, on outages – in past hours. The model accommodates the possibility that consumption in past hours may raise the marginal utility of consumption in the current hour in some demand conditions and lower it in others. The model is similar to the model of demand with inventories in Hendel and Nevo (2006): instead of a cost of storage, consumers have imperfect substitution or complementarity between current and past consumption; and, rather than facing uncertainty in future prices, here consumers face uncertainty in the future availability of power.

The utility from electricity consumption, e_t, in hour t is

$$U(\phi_t, e_t, \mathbf{d}_t, \varepsilon_t, c_t, p; \theta) = \phi_t(u(e_t, \mathbf{d}_t, \varepsilon_t; \theta) + g(e_t, c_t; \theta) - f(p, e_t; \theta)), \tag{1.8}$$

where $u(e_t, \mathbf{d}_t, \varepsilon_t; \theta)$ describes the relationship between e_t and within-hour observed and unobserved demand conditions, $\mathbf{d}_t$ and ε_t, respectively; $g(e_t, c_t; \theta)$ the relationship between e_t and past consumption, c_t; and $f(p, e_t; \theta)$ the price sensitivity. While the price of electricity, p, changes periodically in response to regulation, (1.8) omits the t subscript to emphasize that price variation is not part of the dynamic decision process described in the model. I assume that $U(\phi_t, e_t, \mathbf{d}_t, \varepsilon_t, c_t, p; \theta)$ is bounded, continuous, and strictly increasing in e_t. Finally, θ is a vector of parameters that will be estimated.

When the power is on in hour t, ϕ_t takes the value of one and allows the consumer to consume electricity up to its contracted maximum load $\bar{e}$. When the power is off in hour t, ϕ_t takes the value of zero and restricts consumption and utility to zero, the utility of the outside good. In this sense, e_t is censored: the consumer's choice of e_t determines actual consumption only when the power is available. The censoring of e_t that results from quantity rationing can be seen as a dynamic representation of models of demand under rationing in Deaton (1981) and Lee and Pitt (1987). In those models, quantity rationing constrains consumers away from their optimal bundle of goods and causes them to reallocate consumption among available goods. Here, quantity rationing causes consumers to go off their optimal path of consumer through time and reallocate consumption to periods during which electricity is available.

The interdependence between current and past-period consumption described in $g(e_t, c_t; \theta)$ introduces dynamics into the consumer's decision. Electricity consumption in the current hour may be a substitute or a complement for electricity consumption in other hours. Activities like cooling and water heating are likely to demonstrate imperfect substitutability through time. In the case of space cooling, the room temperature will rise while the power is out. When the power returns, cooling the room to the original temperature prior to the outage will require additional energy input relative to a counterfactual in which the power did not go out.

On the other hand, discrete activities that require continuous input of electricity are likely to demonstrate the complementarity through time. Consider an example: A consumer plans to watch a live television program for an hour, but the power is out for the first half of the hour. Having missed the first half of the program, the consumer may forgo watching the second half when the power returns, reducing her consumption in the second half of the hour relative to what she would have consumed if the power had been on throughout the hour. This simple example illustrates how these intertemporal relationships may be quite complex, which is reflected in the patterns shown in Figure 1.5. If the consumer watches the program when it is aired again later that evening, for example, then the electricity consumption associated with watching the program is complementary over some hours (i.e., during the second half of the hour in which it was originally aired) and substitute over others (i.e., during the later period in which it was re-aired).

1.5.1 State variables and transitions

The state variables of the consumer's dynamic decision include the availability of power in the current period, past consumption, current demand conditions, and the marginal price of electricity. The state vector in period t is denoted,

$$\mathcal{S}_t = (\phi_t, c_t, \mathbf{d}_t, \varepsilon_t, p).$$

Frequently I will also use the notation s_t to describe the deterministic state variables,

$$s_t = (c_t, \mathbf{d}_t, p).$$

The availability of power in the current period, ϕ_t, follows an exogenous first-order Markov process conditional on hour and month of year:

$$P(\phi_{t+1} = 1 \mid \phi_t, h_t, m_t). \tag{1.9}$$

The consumer only chooses consumption in hours in which the power is on, and therefore the probability distribution over future outages is conditional on $\phi_t = 1$. Empirically, the probability of the power going out in the next hour when the power is on in the current hour, $P(\phi_{t+1} = 0 \mid \phi_t = 1, h_t, m_t)$, is very low, generally less than .01. However, the probability that the power stays out for a subsequent hour once it is out in the previous hour, $P(\phi_{t+\tau+1} = 0 \mid \phi_{t+\tau} = 0, h_t, m_t)$, may be above .6, as the mean outage duration is longer than three hours.

Past consumption, c_t, is the endogenous state variable. The evolution of c_t is

$$c_{t+1} = \delta c_t + \phi_t e_t, \tag{1.10}$$

where δ describes the decay in the effect of past consumption on the marginal utility of current-hour consumption. The parameter δ determines the persistence of past consumption choices and outages on current period consumption. The larger δ, the more periods are required to return to optimal c_t following an outage. Because ϕ_t is a random variable, the transition of c_t described above is stochastic: when the power is out in period t, $\phi_t = 0$, and

$c_{t+1} = \delta c_t$. However, in each non-censored period the power is on, $\phi_t = 1$, and the transition of c_t to the next period is deterministic:

$$c_{t+1} = \delta c_t + 1 \cdot e_t. \tag{1.11}$$

The exogenous state variables include observed demand conditions, $\mathbf{d}_t$, unobserved demand conditions, ε_t, and the marginal price of electricity p. Observed demand conditions include the hour of the day and month of the year, as well as the weather. The unobserved demand conditions are observed to the consumer when choosing e_t but not the researcher and are independently and identically distributed in each hour. Finally, the marginal price of electricity is a state variable. Prices change approximately one to two times a year, and I assume that prices are fixed during the decisionmaking horizon in each hour.

1.5.2 Optimal Consumption under Outages

In each hour, the consumer solves

$$\max_{e_t(\mathcal{S}_t)} \sum_{t=1}^{T} \beta^{t-1} E\left[\phi_t(u(e_t, \mathbf{d}_t, \varepsilon_t; \theta) + g(e_t, \mathbf{c}_t; \theta) - f(p, e_t; \theta)) \mid \mathcal{S}_t\right], \tag{1.12}$$

$$\text{s.t. } \; e_t \geq 0,$$

where $E[\cdot]$ is the expectation operator over the distribution of state transitions, specifically ϕ_t and ε_t, and $\beta \in [0, 1]$ is an hourly discount factor. Given the definition of states from the previous section, the optimal policy is Markov, a mapping from the state, $\mathcal{S}_t$, to electricity consumption e_t.

Solution by backward induction

I solve for the optimal consumption policy by backward induction. In this procedure, I solve for the optimal policy in the terminal period, T, and then iterate backward to t. The optimal policy in the terminal period is determined by the first order condition from

$$V(\mathcal{S}_T) = U(s_T; \theta) = \phi_T \left(\max_{e_T(s_T)} \; u(e_T, \mathbf{d}_T, \varepsilon_T; \theta) + g(e_T, \mathbf{c}_T; \theta) - f(p, e_T; \theta) \right), \tag{1.13}$$

$$\frac{\partial u(e_T, \mathbf{d}_T, \varepsilon_T; \theta)}{\partial e_T} + \frac{\partial g(e_T, \mathbf{c}_T; \theta)}{\partial e_T} = \frac{\partial f(p, e_T; \theta)}{\partial e_T}, \tag{1.14}$$

where $V(\mathcal{S}_T)$ is the value function of state $\mathcal{S}_T$. The problem for the previous period is then a Bellman equation,

$$V(\mathcal{S}_{T-1}) = \max_{e_{T-1}(s_{T-1})} u(e_{T-1}, \mathbf{d}_{T-1}, \varepsilon_{T-1}; \theta) + g(e_{T-1}, \mathbf{c}_{T-1}; \theta) - f(p, e_{T-1}; \theta) + \beta V(\mathcal{S}_T). \tag{1.15}$$

Then rewrite $V(\mathcal{S}_T)$, the value of the terminal state, as an expectation over the state transition of ϕ_t and the realization of ϵ_t:

$$V(\mathcal{S}_{T-1}) = \max_{e_{T-1}(s_{T-1})} u(e_{T-1}, \mathbf{d}_{T-1}, \varepsilon_{T-1}; \theta) + g(e_{T-1}, \mathbf{c}_{T-1}; \theta) - f(p, e_{T-1}; \theta) + \beta \int V(s_T) P(\phi_T \mid s_{T-1}) d(\varepsilon). \tag{1.16}$$

$V(s_T)$ is the utility realized from the optimal policy in the terminal state, and it is a function of e_{T-1} through the transition of the endogenous state variable, c_t:

$$V(s_T) = V(c_T, \mathbf{d}_T) = V(\delta c_{T-1} + e_{T-1}, \mathbf{d}_T), \tag{1.17}$$

Noting that, from (1.10), when the decision is uncensored in t, the power is on and $\phi_t = 1$. Rewriting $V(s_T)$ in the Bellman equation in (1.16),

$$\begin{aligned} V(\mathcal{S}_{T-1}) = \max_{e_{T-1}(s_{T-1})} & \; u(e_{T-1}, \mathbf{d}_{T-1}, \varepsilon_{T-1}; \theta) + g(e_{T-1}, \mathbf{c}_{T-1}; \theta) - f(p, e_{T-1}; \theta) + \\ & \beta \int V(\delta c_{T-1} + e_{T-1}, \mathbf{d}_T) P(\phi_T \mid s_{T-1}) d(\varepsilon). \end{aligned} \tag{1.18}$$

(1.18) is now a function of only the current state variables, the policy, and the parameters. The optimal policy as a function of the state variables is given by first order condition,

$$\begin{aligned} & \frac{\partial u(e_{T-1}, \mathbf{d}_{T-1}, \varepsilon_{T-1}; \theta)}{\partial e_{T-1}} + \frac{\partial g(e_{T-1}, \mathbf{c}_{T-1}; \theta)}{\partial e_{T-1}} + \\ & \qquad \beta \int \frac{\partial V(\delta c_{T-1} + e_{T-1}, \mathbf{d}_{T-1})}{\partial e_{T-1}} P(\phi_T \mid s_{T-1}) d(\varepsilon) = \frac{\partial f(p, e_{T-1}; \theta)}{\partial e_{T-1}}. \end{aligned} \tag{1.19}$$

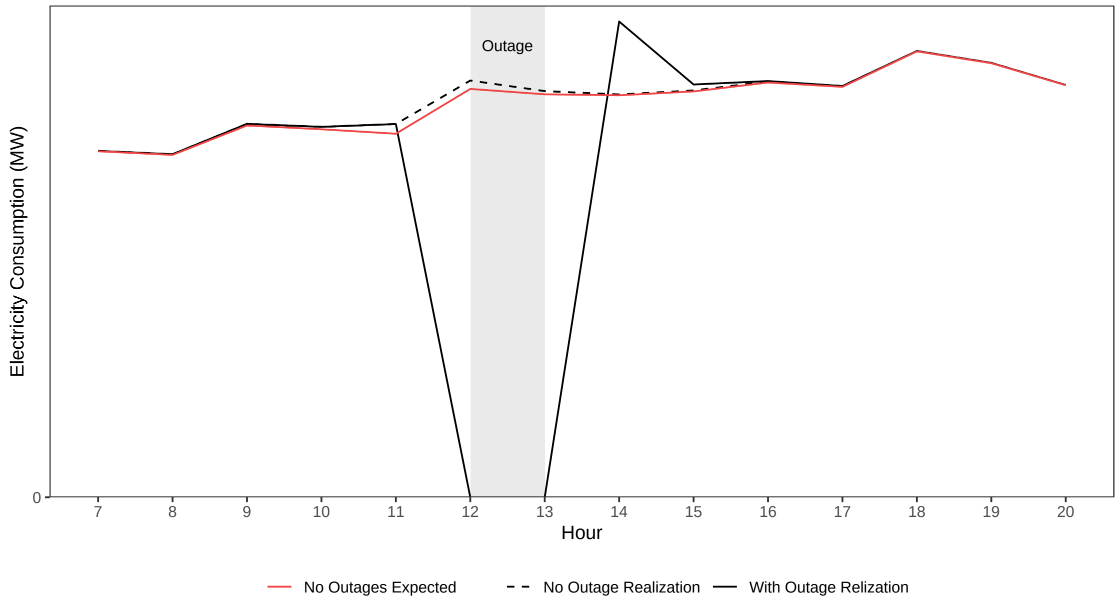
I iterate backward to t, in each period replacing the value function $V(\mathcal{S}_T)$ with the function defined by the relation in (1.19).

Discussion

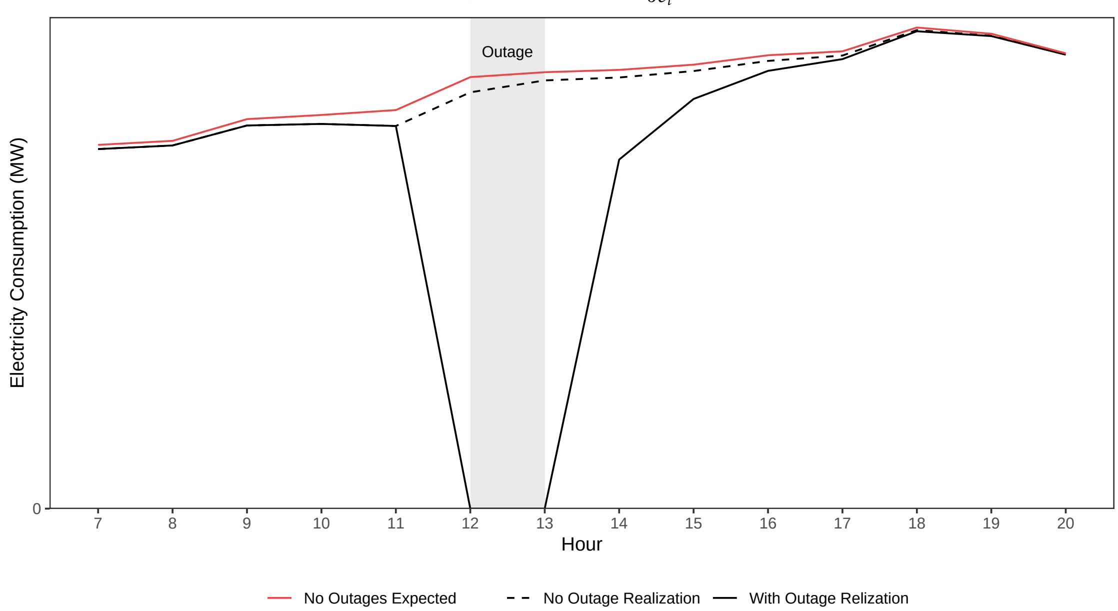
Figure 1.6 illustrates the main mechanisms operating in the model for a sequence of states under hypothetical parameter values and outage probabilities. The top panel shows a case in which consumption is intertemporally substitutable, i.e., $\frac{\partial g(e_t, c_t; \theta)}{\partial c_t} < 0$. The bottom panel shows a case in which consumption is intertemporally complementary, i.e., $\frac{\partial g(e_t, c_t; \theta)}{\partial c_t} > 0$. Both figures show optimal consumption policies under three scenarios. The dotted black line shows the optimal policy when consumers expect that the probability of an outage is non-zero in every hour, but no outage is realized during this period. The solid black line shows the optimal policy when the consumer has the same set of expectations but an outage is realized in hours 12 and 13. Finally, the red line shows optimal policy when the consumer believes there is zero probability of an outage in any hour and no outage is realized in any hour.

Figure 1.6: *Illustration of Optimal Consumption Paths Under Alternative Outage Expectations and Realizations*

(a) "substitutes": $\frac{\partial g(e_t, c_t; \theta)}{\partial c_t} < 0$



(b) "complements": $\frac{\partial g(e_t, c_t; \theta)}{\partial c_t} > 0$



The figure presents an illustration of optimal consumption patterns in the model under alternative outage expectations and realizations. The top panel shows a case in which past consumption, c_t, raises the marginal utility of current consumption, e_t, referred to as substitutes. The bottom panel shows a case in which past consumption reduces the marginal utility of current consumption, referred to as complements. The solid black line shows a scenario in which the consumer has probabilistic expectations about outages and an outage is realized in hours 12 and 13. The dashed black line shows a scenario in which the consumer has the same probabilistic expectations about outages but no outage is realized. The solid red line shows a scenario in which the consumer believes the probability of an outage is zero in all periods and no outage is realized.

The clearest contrast between the two cases is the response in hours 14 through 16, immediately following the outage in hours 12 and 13. In the substitutes case, consumption in hour 14 rises substantially above that of the no-outage scenarios as the consumer compensates for lost consumption. On the other hand, in the complements case, consumption following the resumption of power availability falls relative to the no-outage scenario and persists at a lower level for several hours.

Outages affect consumption differentially across the substitutes and complements cases not only through c_t, but also through expectations. The assumed outage probabilities are the same across the two scenarios, and they are highest during the hours when the outage happens to occur, hours 12 and 13. The divergences between the solid black and solid red line illustrate how consumption responds to the expectation that an outage is more likely in future periods. In the substitutes case, consumption increases in hours 10 and 11 relative to the no outage expectation scenario, reflecting, for example, the consumer front-loading some consumption in anticipation of a possible outage. In the complements case, consumption falls in these hours falls relative to the no outage expectation scenario. When future consumption is a complement to current period consumption, the likelihood of an outage reduces the marginal value of current consumption.

1.6 Estimation

I estimate the model using the hourly feeder-level load data described above in order to evaluate the welfare loss from frequent outages. The estimation procedure uses generalized method of moments (GMM) with a minimum distance criterion. For each candidate parameter vector, θ, the procedure solves for the optimal policy in each state by backward iteration, uses the optimal policies to predict e_t for each observations, and generates moment conditions from the difference between the predicted and observed policies.

1.6.1 Functional forms

I choose functional forms for estimation that accommodate either substitution or complementarity responses to outages, while maintaining a parsimonious representation of the state space. Because the estimation procedure requires computing the optimal policy in each state for each candidate vector of parameters, the size of the state space represents the key computational limitation.

The previous section presents the model for a single consumer. I estimate the model at the feeder level, m, separately for the four customer categories with the highest levels of outages, agriculture, rural mixed agriculture and residential, rural residential, and urban, and separately. Feeders within each category are assumed to be homogeneous after standardizing by the mean load on each feeder via the following the transformation:

$$e_{m,t} = \frac{l_{m,t}}{\frac{1}{T_m}\sum_1^{T_m} l_{m,t}}, \tag{1.20}$$

where $l_{m,t}$ is the load in MW on feeder m in year-month-day-hour t and T_m is the total number of observations for feeder m. This is an alternative to adding feeder fixed effects, which would increase the state space by a factor of the number of feeders.

To further reduce the number of optimal policy computations for each candidate parameter vector, I estimate the model separately for each month of year. The functional forms for the utility function are

$$\begin{aligned} u(e_t, \mathbf{d}_t, \varepsilon_t; \theta) &= (\alpha^h + \varepsilon_t)\ln e_t, && (1.21)\\ g(e_t, c_t; \theta) &= \alpha^{e,c} c_t \ln e_t, && (1.22)\\ f(p, e_t; \theta)) &= \alpha^p p e_t, && (1.23) \end{aligned}$$

so that

$$U(\phi_t, e_t, \mathbf{d}_t, \varepsilon_t, c_t, p; \theta) = \phi_t\left[(\alpha^h + \varepsilon_t)\ln e_t + \alpha^{e,c} c_t \ln e_t - \alpha^p p e_t\right]. \tag{1.24}$$

The shape of consumption within a day is captured in four 6-hour blocks,

$$\alpha^h = \mathbf{1}\{h_t \in (1,\ldots,6)\}\alpha^{h1} + \mathbf{1}\{h_t \in (7,\ldots,12)\}\alpha^{h2} + \mathbf{1}\{h_t \in (13,\ldots,18)\}\alpha^{h3} + \mathbf{1}\{h_t \in (19,\ldots,24)\}\alpha^{h4}.$$

The parameters to be estimated are:

$$\theta = (\delta, \beta, \alpha^h, \alpha^{e,c}, \alpha^p). \tag{1.25}$$

1.6.2 Transitions of ϕ_t

The state transitions of ϕ_t are estimated separately for each category from the empirical frequencies of next-period outages conditional on current period availability of power:

$$\hat{P}(\phi_{t+1} = 1 \mid \phi, h) = \left(\sum_{t=1}^{T_m} \mathbf{1}\{h_t = h\} \cdot \mathbf{1}\{\phi_t = \phi\} \right)^{-1} \sum_{t}^{T_m} \phi_{t+1} \mathbf{1}\{h_t = h\} \cdot \mathbf{1}\{\phi_t = \phi\}. \tag{1.26}$$

For each category-month, there are 48 such estimated probabilities.

1.6.3 Computation of optimal policies based on fitted value function iteration

The procedure for computing the optimal policy for each candidate vector of parameters is:

1. **Estimate c_t for each observation**: Computing optimal policies requires making an assumption about the starting value of c_t for each feeder. I assume that c_t decays to zero after T periods, where T is the horizon over which consumption decisions are made. In the reported results, T is 24 hours. Hence, conditional on a candidate delta the value of c_t is a function of lagged consumption:

$$\hat{c}_{m,t}(e_{m,t-1}, \ldots, e_{m,t-T}; \delta) = \sum_{z}^{T} \delta^z \phi_{m,t-z} e_{m,t-z}. \tag{1.27}$$

2. **Discretize c_t based on $\hat{c}_t$**: In order to compute value functions numerically for values of c_t, I discretize c_t into 50 equally-sized bins ranging from 0 to twice the maximum value of $\hat{c}_t$.

3. **Compute the value in the terminal period, $\hat{V}_T(e_T(c_T))$**. I compute the value function for the terminal period in each state based on the FOC in (1.14). I then smooth the discrete value function over c_t using a local linear regression for each hour-price pair.

4. **Iterate backward**. To iterate backward I maximize numerically the empirical analogue to (1.18),

$$\max_{e_{T-1}} (\alpha^h + \varepsilon_t) \ln e_{T-1} + \alpha^{e,c} c_t \ln e_{T-1} - \alpha^p p e_{T-1} + \hat{V}_T(\delta c_t + e_t) \hat{P}(\phi_T = 1 | \phi_{T-1} = 1 \cap \phi_t = 1), \tag{1.28}$$

repeating this step backward to t.

5. **Predict** $\hat{e}_t(c_t, h, p; \theta)$**.** The optimal policy in t is given by the maximizer of the value function in t, $\hat{V}_t(e_T(c_T))$. I smooth the optimal values of e_t over the range of c_t again using a local linear regression for each hour-price pair. The predicted value from this local linear regression provides a predicted consumption level for each feeder-hour, $\hat{e}_t(c_t, h, p; \theta)$.

1.6.4 Estimation by GMM

The estimation procedure minimizes the L2 distance of the predicted and observed standardized consumption levels, $\hat{e}_t(c_t, h, p; \theta)$ and $e_{m,t}$, respectively. I construct hourly moment conditions, as well as the difference between predicted and observed consumption levels interacted with lagged outages. The moment conditions are:

$$\psi(\theta) = E \begin{pmatrix} |\hat{e}_t(c_t, h, p; \theta) - e_{m,t}|_2 \cdot \mathbf{1}\{h_t = 1\} \\ \vdots \\ |\hat{e}_t(c_t, h, p; \theta) - e_{m,t}|_2 \cdot \mathbf{1}\{h_t = 24\} \\ |\hat{e}_t(c_t, h, p; \theta) - e_{m,t}|_2 \cdot (1 - \phi_{m,t-1}) \\ |\hat{e}_t(c_t, h, p; \theta) - e_{m,t}|_2 \cdot (1 - \phi_{m,t-2}) \\ |\hat{e}_t(c_t, h, p; \theta) - e_{m,t}|_2 \cdot (1 - \phi_{m,t-3}) \end{pmatrix} = 0. \tag{1.29}$$

Then the estimator is:

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmin}} \left(N^{-1} \sum_t \hat{\psi}(\theta) \right)' \hat{W} \left(N^{-1} \sum_t \hat{\psi}(\theta) \right), \tag{1.30}$$

where $\hat{W}$ is an identity weight matrix and N is the number of observations for the sample.

1.6.5 Identification

I expect that the moments with the lagged outage help to separately identify δ from α_{ec}. The identifying variation for δ in the data comes from comparing current period consumption for alternative outage patterns, holding all other values of the state variables fixed. In other words, δ captures the rate of decay in response to an outage over hours, holding all else fixed. Price sensitivity is identified from price changes within months and across feeders.

1.7 Results

Table 1.5: *Parameter Estimates for February, 2017 and 2018*

	Agriculture (1)	Rural Mixed (2)	Rural Residential (3)	Urban (4)
δ	0.0365	0.143	0.2	0.143
	(0.7238)	(0.0433)	(0.0696)	(0.3454)
α^{h1}	0.816	0.765	0.842	0.781
	(0.1309)	(0.0511)	(0.3925)	(0.2673)
α^{h2}	0.954	1.147	1.38	1.164
	(0.0712)	(0.1588)	(0.4520)	(0.1831)
α^{h3}	0.943	2.066	1.347	1.363
	(0.0298)	(0.0313)	(0.0077)	(0.3568)
α^{h4}	0.921	1.147	1.208	1.427
	(0.1232)	(0.0941)	(0.0976)	(0.1952)
α_{ec}	-0.196	-0.0432	0.07	-0.017
	(0.0024)	(0.0532)	(0.0114)	(0.3702)
α_p	0.524	0.188	0.166	0.152
	(0.3248)	(0.0957)	(0.1151)	(0.1659)
Observations	236,651	322,035	315,150	306,832

The table reports model parameter estimates for the months of February 2017 and 2018 using samples of the full load time series from 500 feeders in each customer category. Differences in the number observations reflects both differences in outage frequencies and differences in data coverage.

Given that the estimation algorithm requires computing the solution by backward induction for each state for each iteration of the minimization over θ, the procedure is computationally intensive. I estimate the model separately for each customer category in each month of the year for 2017 and 2018 for a horizon of 24 hours ($T = 24$) in order to reduce the size of the space of discrete states, (m, h, p), by removing month. This has the effect of interacting all of the parameter estimates with the month, and the size of the resulting state space is the number of hours, 24, times the number of unique prices, which is between 2 and 4. For each category, I draw a random sample of the complete time series of 500 feeders. The resulting samples for each month of year in 2017 and 2018 range between about 236,000 and 322,000 across the categories. The estimates constrain β to one due to difficulty identifying the parameter in early model runs, a common issue with many similar models. The effect of this is to load discounting into the α_{ec} and δ parameters.

The parameter estimates are presented in Table 1.5. Agricultural consumers, which are primarily irrigation pumpsets, have the highest degree of intertemporal substitutability, with an α_{ec} of -.196. Rural residential customers, on the other hand, have somewhat intertemporally complementary consumption, with an α_{ec} of .07. The load patterns of rural residential customers in the data show dramatic variation between within-day peak and off-peak consumption, likely because many of these households own few always-on appliances like refrigerators. In most cases their largest loads are likely to be lighting, which is difficult to shift in time in response to an outage. Urban residential consumers also have somewhat more flexible consumption, with an α_{ec} of -0.017. This may reflect larger stocks of appliances like refrigerators and air conditions, which require additional energy input to return to their original settings following an outage. Agricultural consumers are much more price sensitive than the other categories (α_p) and experience less persistence in shocks to consumption due to outages (δ).

The patterns of parameter estimates are consistent with the results from the descriptive evidence section. Agricultural consumers appear quite adapted to regular outages: they are able to shift consumption and return to their optimal path of consumption quickly. Moreover, these consumers are the most price sensitive, and hence most willing to trade reliability for subsidy.

1.7.1 Estimates of the Welfare Loss from Frequent Power Outages

I characterize the welfare loss from power outages in terms of a measure similar to compensating variation. In particular, I estimate the magnitude of the price increase that would hold consumers' utility fixed under a counterfactual with no load shedding. These counterfactuals use the estimated parameters, and allow consumers to choose a new sequence of e_ts in a scenario with no load shedding outages. The effective price is estimated as follows:

1. **Calculate utility for the realization of states under the estimated parameters.** The realized utility is:
$$\bar{U} = \int U(\phi_t, e_t, \mathbf{d}_t, \varepsilon_t, c_t, p; \hat{\theta}) d(\hat{\mathcal{S}}_t), \tag{1.31}$$
where $d(\hat{\mathcal{S}}_t)$ is the distribution of realized states in the data.

2. **Calculate utility for the counterfactual in which no outages are realized.** The counterfactual utility with no outages is,
$$\bar{U}^c = \int U(1, e_t, \mathbf{d}_t, \varepsilon_t, c_t, p; \hat{\theta}) d(p, \mathbf{d}_t), \tag{1.32}$$
where $d(p, \mathbf{d}_t)$ is the realization of deterministic states in the data. In this scenario, consumers choose a new sequence of consumption, e_t, under the same prices but with no outages, reaching a higher level of utility.

3. **Increment p upward and recompute $\bar{U}^c$.** I proceed iteratively, incrementing p^c, the counterfactual price, upward in small steps until $U^c = \bar{U}$.

Table 1.6 presents the results of the welfare analysis. The first row, Percentage Price Increase, shows the percentage price increase that equalizes utility under the status quo and the no-outage scenario. The second row divides the price premium by the average duration of outages in hours in an average month. For agriculture, about 70 hours of outages per month have the equivalent effect on utility of raising the price by about 72.1 percent, the highest among all categories. However, on a per-hour basis, the welfare cost to agriculture is lowest among the groups. Urban consumers bear more than 5 times the cost per hour of outage than agriculture, at 5.87 percent per hour each month.

Table 1.6: *Welfare Estimates: Percentage Price Increase to Equalize Realized and No-Outage Utility*

	Agriculture (1)	Rural Mixed (2)	Rural Residential (3)	Urban (4)
Percentage Price Increase	72.1	37.5	22.8	19.7
Per Outage Hour	1.02	2.79	2.61	5.87

The table reports results from the welfare calculation based on model parameter estimates for February 2017 and 2019 presented in Table 1.5. The top row is the percentage increase in price that would result in a welfare loss equivalent to that from realized power outages, relative to the feeder-level observed marginal price observed in the data. The bottom row presents the same figures on a per average hour of outage in the months of February 2017 and 2018.

1.8 Conclusion

This analysis documents the striking cost of power outages to consumer welfare in Maharashtra. I find evidence that power outages significantly undermine the value of electricity subsidies across MSEDCL's subsidized customer categories. The results suggest that much of the customer base would be better off under substantially higher electricity prices if MSEDCL could deliver a higher level of reliability.

However, the results also suggest that, from an efficiency perspective, load shedding outages are remarkably well targeted. Urban consumers lost about 5.8 times what agricultural consumers lost in welfare per hour of outage, and agricultural consumer received about 20 times as many outages as urban consumers. Given the short-run horizon of this analysis, it raises a question about how consumers adapt in the long run to patterns of outages. In the longer run, as consumers adapt their appliance and other capital investment decisions to the availability of electricity as a complement to their assets or an input to production, I might expect these effects to be even larger.

Chapter 2

Short- and Long-Run Consumption and Non-Payment Responses to Retail Electricity Prices in India[1]

2.1 Introduction

Throughout the world, many public utility companies providing services like electricity, water, transportation, and sanitation find themselves in a political-economic equilibrium characterized by poor service quality and poor financial performance. This equilibrium is perpetuated by a self-reinforcing cycle in which regulated prices set below cost deprive utility companies of the resources needed to maintain high levels of service quality. In turn, poor service quality undermines the value of these services to the public and the ability of policymakers to justify raising prices or maintaining high levels of support from general tax revenues. In some cases, widespread non-payment or outright theft of public services exacerbates this cycle.

For decades India's electricity distribution segment has struggled to rise from a deep infrastructure quality trap. As of 2019, the approximately 100 utility companies serving

[1]Co-authored with Shefali Khanna

retail customers across the country collectively held about USD 56 billion in outstanding debt, equivalent to 1.9 percent of India's GDP (ETEnergyWorld, 2020). While many of these utilities have managed to improve service quality in recent years, grid capacity shortfalls and deferred maintenance mean that hundreds of millions of people likely experience more than 10 hours of power outages every day (Aklin et al., 2016). In spite of deeply subsidized retail price schedules for residential and agricultural customers, these utilities have long faced extreme rates of non-payment and pilferage. In 2019 the utilities collected revenue on only about 77 percent of the kilowatt hours (kWh) they served to customers, with the gap reflecting a combination of technical grid losses, failures to bill customers, and non-payment of bills (Power Finance Corporation Ltd., 2020). For several utilities, these losses were as high as nearly 40 percent.

Recent research on this topic has pointed toward highly subsidized retail prices as a root cause of dysfunction in electricity distribution in settings like India (McRae, 2015; Burgess et al., 2020). The authors of both of these papers argue for dramatically reducing retail subsidies for electricity, which amount to 50 percent or more of the average cost of supplying power to customers served by many of India's utilities. Under these policy prescriptions, raising retail prices could increase welfare by eliminating distortions, improve the finances of electric utilities, and, as a result, support investment in better service quality. However, such reforms would also come at a cost. India, like many other countries with large informal sectors and poorly developed income tax systems, relies heavily on commodity price subsidies for income redistribution to the poor (Gadenne, 2020). As a consequence, policymakers have limited means for achieving similar degrees of redistribution through potentially more efficient policy mechanisms. Moreover, by reducing affordability, pricing reforms may worsen non-payment.

In order to evaluate these potential costs and benefits of retail electricity pricing reform, this paper provides empirical evidence on the consumption and non-payment responses of electricity customers to retail prices in Delhi, India. Beginning in the late 1990s, Delhi pursued an ambitious set of reforms to its electricity sector that included partially privatizing its distribution segment, formalizing the connections of hundreds of thousands of informal settlement customers, incentivizing investments in improved reliability and service quality, and approximately tripling average retail electricity prices over a decade. Local elections in 2015 brought a populist government in to power in part on promises of reversing these price increases. During the period we study, 2015 to 2019, the government reduced average prices for residential customers by 10 to 18 percent, with small residential customers receiving the largest reductions.

Our empirical strategies take advantage of features of Delhi's highly complex retail electricity price schedule to estimate short-run and long-run responses to price changes. Using confidential data including records of about 79 million individual electricity bills, we reconstruct the monthly payment histories of more than 1.5 million domestic, informal settlement, commercial, and small industrial electricity customers served by one of Delhi's three utilities. Pricing reforms beginning in 2014 introduced large notches in the marginal price schedule, and we use a regression discontinuity estimator to analyze the short-run response of customers to non-marginal increases in the average cost of electricity resulting from these subsidy notches. We find that the leading one to three months' consumption of consumers who are exposed to dramatic non-marginal price increases as a result of consuming above a subsidy notch are very insensitive to these large price increases. For residential customers, the implied elasticities of these estimates range between -.013 and -.0349. However, during these periods arrears among affected customers rise substantially, though transiently.

We then turn to the long run, employing an instrumental variables (IV) strategy to estimate price elasticities and non-payment responses to price variation. Our IV strategy exploits a rounding rule in the electricity price schedule that generates minute but sustained, plausibly-exogenous variation average electricity prices. We estimate annual price elasticities separately in deciles of annual consumption for domestic and informal settlement customers, and in quintiles for commercial and industrial customers. We find large elasticities across the customer base, ranging from about -.6 in the top decile of informal settlement customers to -1.99 in the top quintile of industrial customers. We also find significant annual responses of non-payment to average prices, with effects concentrated among the lower four deciles of domestic and informal settlement customers. For instance, for the bottom decile of informal settlement customers, average arrears more than double in response to a doubling in the average electricity price.

Retail price elasticity estimates are generally available in rich country settings (Borenstein, 2010; Wolak, 2011; Ito, 2014; Jessoe and Rapson, 2014; Deryugina et al., 2020). However, well-identified estimates for developing country settings are much sparser. The literature has also generally focused on estimating short-run demand elasticities given the difficulty of finding long-run exogenous variation in energy prices. Long-run elasticity estimates that do exist use state-level data and dynamic panel models rather than quasi-experimental variation (Kamerschen and Porter, 2004; Dergiades and Tsoulfidis, 2008; Alberini and Filippini, 2011). Deryugina et al. (2020) estimate two-year responses to electricity prices in Illinois and find that households gradually respond to changes in electricity prices. In this paper, we use notches generated in the retail electricity tariff structure by the introduction of subsidies three times during our sample period to examine the short-run consumption response. We are also able to estimate long-run elasticities using minute time series and cross-sectional variation in the effective electricity price schedule generated by differences in billing cycles and a quirk in the standardization factor used to ensure that consumers face approximately the same price schedule for each unit of consumption. Furthermore, we use these strategies to estimate a negative payment elasticity to the price, which suggests that subsidizing power may generate surplus by raising payment rates.

The subsidies introduced by the Delhi government not only dramatically reduced electricity prices for most residential customers, they also increased the complexity of the price schedule. Standard welfare analysis assumes that consumers can distinguish between fixed and variable costs. However, empirical evidence suggests that consumers may misconceive a change in average price as a change in marginal price Liebman and Zeckhauser (2004). In the case of electricity markets, Ito (2014) finds that consumers respond to average price rather than marginal price, when the marginal price is a step function of monthly consumption, similar to multi-tiered income tax schedules. Monthly electricity consumption is also often difficult to observe, making it challenging to optimize against complex non-linear price schedules (Borenstein, 2009; Jessoe and Rapson, 2014). While notches in tax schedules have been shown to magnify the behavioral responses to the underlying taxable income elasticity Kleven and Waseem (2013), the lack of salience and optimization failures could mitigate the response to the subsidy. In this paper, we also consider how non-payment affects consumers' response to complex non-linear price schedules and illustrate how the role of nonpayment in determining the welfare effects of subsidies depends on the functional form of electricity demand and the collection enforcement regime.

The rest of this paper proceeds as follows. Section 2.2 describes the institutional setting and electricity pricing in Delhi. Section 2.3 presents our data, describes the approach used to infer customer payments from the billing data, and analyzes descriptive statistics. Section 2.4 describes the empirical strategy and presents results for short-run responses to the subsidy notches. Section 2.5 describes the empirical strategy and presents results for the long-run responses. Finally, 2.6 concludes with a discussion of the potential policy implications of our findings.

2.2 Electricity Pricing in Delhi

Following major reforms to Delhi's electricity distribution segment beginning in the late 1990s, which are described in greater detail in Chapter 3, retail electricity price rose substantially through the 2000s. Referred to as "tariff rationalization" by DERC, the price increases sought to bring retail prices closer to being cost-reflective while supporting the utilities' investment drive. Between 2002 and 2013, average retail prices for residential consumers more than tripled.

February 2015's Delhi Legislative Assembly elections swept a new populist party, the Aam Aadmi Party, into government in part on the promise of making water free and cutting electricity prices for residential customers by 50 percent. Within weeks of its election, the

AAP-led government announced a 50 percent subsidy on the retail electricity tariff for residential customers consuming up to 400 kWh per month, covering about 86 percent of residential bills (Economic Times, 2015). The subsidies were financed by the government, which reimbursed the utilities for the lost revenue relative to the regulated tariff. On March 1, 2018, the Delhi Electricity Regulatory Commission (DERC) issued a new tariff order with higher fixed charges but lower per-unit rates, which when combined with the AAP government's new INR 2 per unit subsidy for consumption up to 400kWh, increased the average price disproportionately at lower levels of consumption. On May 9, 2018, the Delhi government extended the INR 2 per unit subsidy for customers consuming less than 400kWh per month and approved an additional subsidy of INR 100 on fixed charges for domestic customers consuming up to 100 kWh per month.

As a penalty for failing to pay a bill on time, customers are fined a Late Payment Surcharge at the rate of 18% per year on unpaid dues, which is computed based on the number of days between the payment due date and the date the payment was made. Furthermore, according to the DERC Supply Code 2017, customers are issued a temporary disconnection notice if they do not make pay a bill within three days following the payment due date. The temporary disconnection notice states that the customer will be temporarily disconnected after 15 days if the bill remains unpaid. If the customer is temporarily disconnected, they will no longer receive any power supply, but they will continue to be liable to pay fixed charges to the utility. The service line will remain connected for up to six months, after which the customer will be permanently disconnected if their dues have not been cleared. Once a customer is permanently disconnected, their service line is removed and they can apply for a new connection once all outstanding dues have been cleared. In the summer of 2018, the utility we worked with began replacing traditional meters with smart meters. So far, nearly 200,000 smart meters have been installed. Smart meters enable the utility to remotely disconnect customers and thereby improve enforcement of bill payments.

Fixed charges are levied in proportion to the customer's sanctioned load, which is the load, in kW or kVA, that the utility has agreed to supply the customer. In 2018-19, the fixed charge for a residential connection was INR 125/kW/month for a sanctioned load up to 2kW, INR 140/kW/month for sanctioned load between 2 and 5kW, INR 175/kW/month for sanctioned load between 5 and 15kW, INR 200/kW/month for sanctioned load between 15 and 25kW and INR 250/kW/month for sanctioned load above 25kW. The utility revises the sanctioned 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.

2.3 Data and Descriptive Statistics

The analysis draws on data from two principal sources. First, we obtained billing and power outage records for several years 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 history using their unique customer number. The resulting dataset enables us to observe about four and a half years of billing records in addition to detailed demographics and appliance information for the sample of households surveyed. This section describes each of these two data sources in turn and provides summary statistics for the sample of customers used in estimation.

2.3.1 Data

Electricity Bills and Payments

The utility we study serves more than 1 million customers and issued approximately 79 million bills to the residential, industrial, commercial, and public services customers it serves in an exclusive service territory covering a large swath of central Delhi and its outskirts between mid 2014 and the end of 2018. Customers receive electricity bills from the distribution company on approximately monthly cycles for the prior period of consumption.[2] Typically, bills post two to three days following the close of the billing period, and customers have approximately 14 days to pay their bill. In addition to the total amount payable in Rupees (INR), the customer billing data include total consumption in kilowatt hours (kWh), detailed breakdowns of individual fixed and volumetric charges, subsidies and rebates received, and the due date of the bill.

Because we do not observe payments directly, we impute payment rates and arrears using the sequence of bills received by each customer. Each billing record contains both charges added during the current billing cycle and the total amount payable on the account at the time of posting. The difference between these reflects outstanding balances on the account, which may be either positive or negative. The positive balances reflect either unpaid past-due charges or outstanding charges that have not yet come due. We infer the portion of these positive balances that are past due based on the due dates of each customer's prior bills. This procedure requires several assumptions. First, we are unable to allocate account balances to arrears and outstanding charges that have not yet come due for each customer's first observed bill because we cannot observe the due dates of prior bills. To resolve this problem, we assume that all balances are outstanding charges that have not yet come due. Second, in approximately 95 percent of cases we observe a customer's next bill post following the due date of their prior bill. For these cases, we can observe whether the customer paid the prior bill by the posting date of the next bill, generally about two weeks later, but not whether the customer paid the bill by the exact due date. Therefore, our measure of the payment rate is precisely the payment rate by the next bill posting date, not by the due date. Throughout the analysis, we control for length of billing period effects to account for this. There are two additional caveats that may introduce additional error into the measurement of arrears and payment rates. First, all charges billed by the utility are rounded down to the nearest INR 10 (about USD .13), with the remainder rolled

[2]A small proportion of customers served by the utility have pre-paid meters during the later years of the study period. They are excluded from the analysis here.

over to the next month's amount payable. We do not observe this rounding adjustment factor separately and therefore cannot distinguish it from unpaid balances. Second, we cannot observe interactions with the utility that incur charges not included in the bill. For example, if a customer is required to upgrade their connection for a higher load rating due to the installation of a new appliance, this will not be included in the billing data and will generally result in a large negative payment rate under our imputation. These occurrences are rare, and we control for load changes throughout the analysis. Appendix section B.2 describes in detail the methodology and assumptions used to impute payment rates and arrears using these billing records.

Survey of Residential Electricity Customers

We surveyed 3,181 households in Delhi served by the electric utility 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,[3] 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 bill as part of the survey, enabling us to link their survey responses to their history of electricity bills and outages. 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 –

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

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.

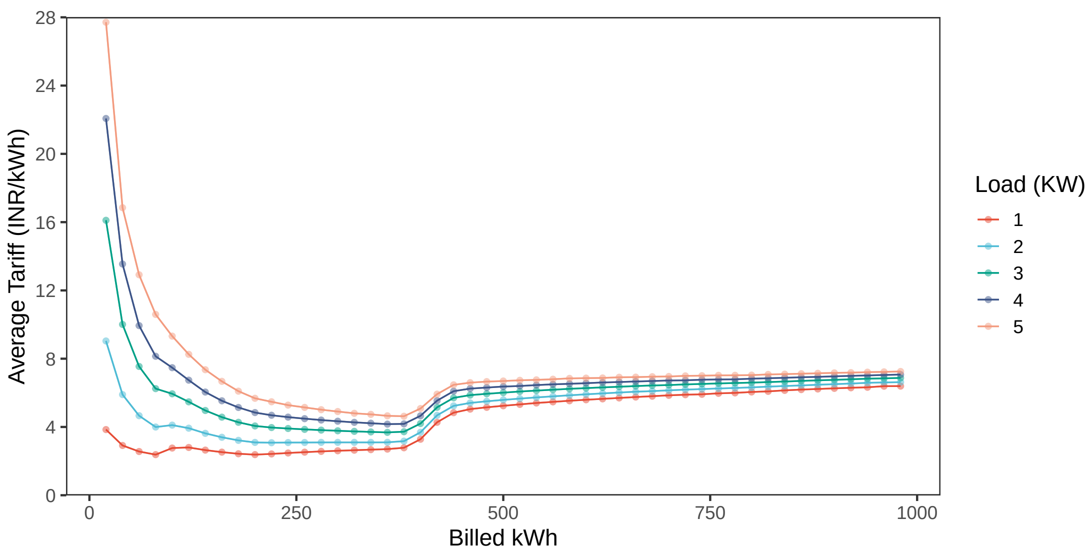
2.3.2 Descriptive Statistics

Electricity Prices

Figure 2.1 plots average prices billed to consumers by sanctioned load for 2018. The vertical axis is the total bill amount divided by the billed kWh, and the horizontal axis is billed kWh on each bill. The points represent the mean of the average tariffs of bills falling in 20 kWh bins. Throughout the study period, the domestic price schedule is determined by a two-part IBT and subsidies. The fixed charge is proportional to the customer's sanctioned load, which reflects the total allowable wattage of connected appliances. During the period represented in the figure, fixed charges ranged from INR 125 per KW per month for residential consumers with sanctioned loads of two KW or less to INR 250 per KW per month for consumers with more than 25 KW. In 2018 about 79 percent of residential customers had a sanctioned load of 2 KW or less and about 92 percent 5 KW or less. The energy charges follow an IBT, beginning at INR 3 per kWh for the first 200 kWh, rising to INR 4.50 per kWh for kWhs 200 to 400, to INR 7 per kWh for kWhs 800 to 1200, and finally to INR 7.75 per kWh for consumption above 1200 kWh. In 2018, about 55 percent of domestic bills fell on the bottom step, another 28 percent on the second step, 13 percent on the third step, 3 percent on the fourth step, and slightly more than 1 percent on the top step. The subsidies introduced by the government at various points then apply to the total energy charges, creating notches in the price schedule. As discussed in the previous section, during 2018 there was a 50 percent subsidy on energy charges for consumption up to 400 kWh and an additional fixed INR 100 subsidy for consumption up to 100 kWh

The combination of the two-part tariff, IBT, and subsidies renders the marginal price schedule extraordinarily complex. Figure 2.2 plots the marginal electricity price for residential consumers by fiscal year from 2014 to 2018, which runs from April through March of

Figure 2.1: *Average Tariff (INR/kWh) Billed to Domestic Customers, By Sanctioned Load (KW), Mean in 20 kWh Bin*

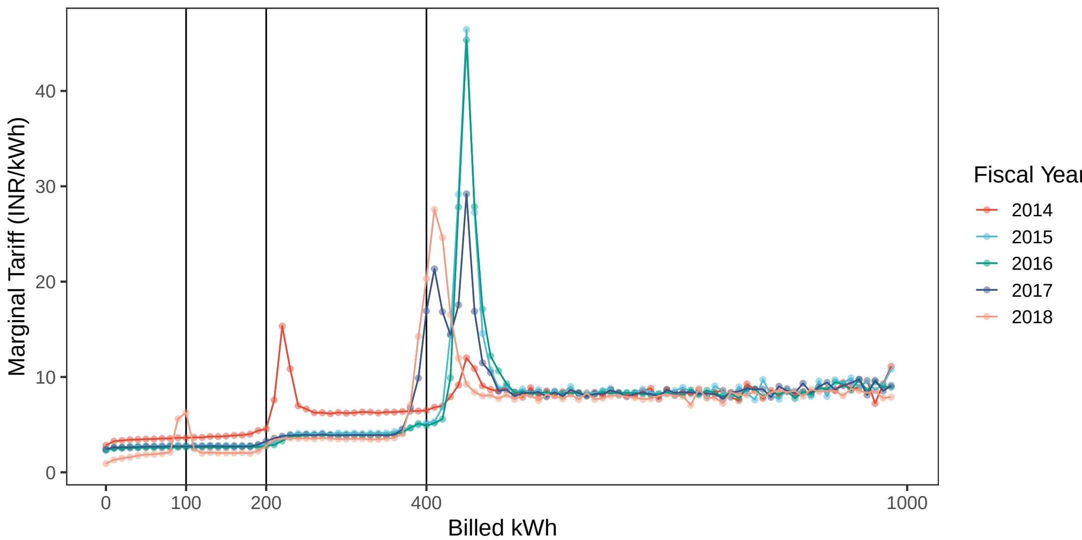


The figure presents the average tariff billed to residential customers (including domestic and informal settlement customers) in INR per kWh by sanctioned load in KW for fiscal year 2018. The points are the mean total billed amount in INR divided by the total billed kWh for bins of 20 kWh. Bins begin at the location of the point in kWh and end at the location of the next point to the right.

the following year. As in Figure 2.1, the horizontal axis represents the quantity consumed in kWh in the month-long billing period. The vertical axis is the empirical marginal tariff in 10 kWh bins, estimated using forward first differences. The most salient feature of the marginal tariff schedules during this period is the spike at 400 kWh, which emerges at the end of fiscal year 2014 in March 2015. As consumers cross the threshold of 400.5 kWh, their total bill amount immediately increases by more than 60 percent on average. During other periods, subsidies at 100 and 200 kWh created similar but smaller spikes. In the figure, the colors correspond to fiscal years, rather than sanctioned load as in Figure 2.1, and show changes in the price schedule during the study period. Only fixed charges vary across residential customers of different sanctioned loads, and therefore the marginal price schedule is largely the same across all residential customers. However, the marginal price schedule is not exactly the same across all residential customers due to the subsidies, some of which are applied on the total bill amount including fixed charges.

Table 2.1 presents summary statistics separately for informal settlement and domestic

Figure 2.2: *Marginal Tariff (INR/kWh) Billed to Domestic Customers 2014 to 2018, by Fiscal Year, in 10 kWh Bins*



The figure presents the empirical marginal tariff billed to residential customers (including domestic and informal settlement customers) in INR per kWh by fiscal year for 2014 to 2018. The marginal tariff is computed by forward first differences in 10 kWh bins.

customers with sanctioned loads of 5 KW or less for fiscal years 2015 to 2018. These customers are subject to the same price schedule. Because domestic customers have larger connected loads and higher average consumption, they paid higher prices during this period. On average, domestic customers paid INR 4.49 per kWh, while informal settlement customers paid INR 3.66 per kWh.

Electricity Consumption and Payment Outcomes

Table 2.1 also presents average consumption and payment outcomes for informal settlement and domestic customers. In the table, consumption is presented per bill day to account for differences in the length of billing periods. On average, informal settlement customers consumed about 58 percent as much electricity per day as domestic customers. They also had substantially higher rates of non-payment and arrears. Informal settlement customers had on-time payment rate of less than .63, compared with .89 for domestic customers. The median informal settlement customer carried arrears of INR 151.2 across their bills in a year, equivalent to about 34 percent of the average total charges on each bill for these customers. The median domestic customer also had arrears on the average bill in a year, totalling INR 55.7 or about 5 percent of their average billed charges.

Non-Payment and Consumption in the Survey Sample

Table 2.2 summarizes non-payment rates and billed electricity consumption by demographics as measured in the survey. The mean payment rate of surveyed customers is about .69, which compares with an average of .76 for the utility's residential customers as a whole. Mean billed electricity consumption for survey respondents is about 177, as compared with 212 for all residential customers.

Panel A reports regression coefficients and customer-clustered standard errors from 10 separate univariate regressions of payment rates (column 1) and billed consumption in kWh (column 2) on demographics at the customer-bill level from September 2014 to March 2019. Installed wattage is an estimate of the total electrical load of all appliances owned by the household, which is calculated from an inventory of appliances. Total installed wattage is calculated using the average wattage of common household appliances and the number of each type of appliance that the surveyed household claims to own. The average installed wattage among surveyed households is 2.8 KW, about equivalent to owning a small refrigerator, a television, two ceiling fans, an electric iron, and several lightbulbs and phone chargers. Billed consumption is strongly correlated with the installed wattage, as are payment rates. The number of rooms in the dwelling and the education of the head of household are also positively correlated with both payment and consumption. Owning one's own dwelling and running a business from the dwelling are not strongly correlated with either outcome.

Panel B reports the mean and standard deviation of payment rates and consumption by income. Income is self reported by respondents, who select one of the eight bins displayed. The median respondent household in the survey reported between 75,000 and 150,000 INR (about 1,000 to 2,000 USD). Delhi's per capita income in 2018-2019 was about 365,000 INR

(4,800 USD), more than three times the national average (Planning Department, Government of NCT of Delhi, 2019).

2.4 Short Run Consumption and Payment Responses to Subsidy Notches

Subsidy policies introduced in 2014, 2015, and 2018 generated large notches in the electricity price schedule for Delhi's residential consumers. The largest of these subsidies was a 50 percent discount on total energy charges for consumption up to 400 kWh. Under this policy, the total energy charges immediately double as consumption rises above a threshold of 400.5 kWh, increasing total bill amounts by about 50 percent on average.[4] A smaller notch at 200 kWh was in effect from September 2014 to February 2015, and one at 100 kWh began in June 2018.

Figure 2.3 plots the distributions of billed kWh throughout the study period separately for domestic and informal settlement customers along with the locations of the three price notches. These plots show consumption in billed kWh adjusted for the start and end date of the billing period. The subsidy policies are defined on the basis of consumption in kWh adjusted by factor called the "slab," which is intended to approximately equalize the location of the IBT steps on a per day basis. The details of this adjustment factor are described in Section 2.5 on long-run responses, which uses slab to construct an instrumental variable for average prices. For domestic customers, the 100, 200, and 400 kWh thresholds fall at the .293, .598, and .834 quantiles of slab-adjusted monthly consumption, respectively, across all bills during the study period. For informal settlement customers, the thresholds fall at the .467, .813, and .972 quantiles, respectively. However, due to substantial seasonality in consumption, the 400 kWh threshold is relevant for a larger proportion of customers than these distributions reflect: about 55 percent of domestic customers and 22 percent

[4]The effect of crossing each subsidy threshold varies across customers of differing sanctioned load, on which fixed charges are based, and through time as various components of the price schedule changed.

of informal settlement customers have at least one bill with more than 400 kWh of billed consumption during the study period.

These subsidies substantially reduced electricity prices for most residential customers in Delhi, but they also introduced additional complexity to the price schedule and, as a consequence, potentially dramatically increase volatility in average bill amounts for customers that did not closely monitor their consumption. Monthly electricity consumption is difficult for consumers to observe and likely subject to a large degree of uncertainty, contributing to the challenge of optimizing consumption against complex non-linear price schedules (Borenstein, 2009; Jessoe and Rapson, 2014). Studying residential electricity consumers in the US and Canada, Ito (2014) and Shaffer (2020) find evidence consistent with customers optimizing against average, rather than marginal, prices under two-part IBTs that are less complex than the tariff schedule studied here.

Behavioral responses to notches in the electricity price schedule have potentially significant implications for the welfare effects of Delhi's electricity subsidy policies. On the one hand, notches in tax schedules have been shown to magnify behavioral responses relative to the underlying elasticity of earnings, resulting in large distortions (Kleven and Waseem, 2013). Uncertainty in future demand and the difficulty observing consumption could magnify these responses further if consumers are unable to bunch precisely below the notch point and instead must reduce their consumption even more to reduce their risk of being subjected to a large increase in the average price. On the other hand, uncertainty, poor observability, and the challenge of optimizing against a non-linear budget constraint with multiple large discontinuities could dampen behavioral responses to the subsidies (Chetty et al., 2009). In this case, lack of salience and optimization failures could reduce the distortion associated with the subsidy notches relative to a simpler policy, like an all-unit discount on variable charges.[5]

Non-payment adds an additional complicating factor to analyzing consumers' responses

[5] In the Chetty et al. (2009) framework, lack of salience is only guaranteed to reduce excess burden when there are no income effects, an assumption that may not be reasonable here.

to complex non-linear price schedules that is not widely considered in the literature. The role of non-payment in determining the welfare effects of these subsidies depends on the form of demand and the collection enforcement regime. To illustrate the possibilities, we consider three alternative collection regimes under isoelastic demand and a linear price for electricity, p. If a customer believes that she can maintain a fixed rate of payment, $c \in (0, 1]$, then the effective price is $p \cdot c \leq p$. Under this regime, the quantity demanded increases with the rate of non-payment, $1 - c$, in proportion to the elasticity. Similarly, when the price changes, the quantity demanded will adjust in proportion to the elasticity. By construction unpaid bill amounts will rise with prices. Second, consumers might alternatively believe that they can only maintain a fixed level of non-payment per unit, $n \in [0, p)$, so that the effective price is $p - n$. With isoelastic demand, the magnitude of the behavioral response to price changes will increase with n. Under this regime, unpaid bills decrease with prices: the amount unpaid per unit is fixed at n, but the quantity demanded falls with prices, reducing the product. Finally, perhaps consumers believe that the total amount of unpaid charges per bill is fixed at $a > 0$. This collection regime will dampen behavioral responses to price changes. When prices rise, reducing quantity enables additional unpaid charges per unit, mitigating the price increase. When prices fall, increasing quantity raises the effective price by reducing the amount of unpaid charges per unit.

This section examines customers' consumption and payment responses to Delhi's 2014, 2015, and 2018 subsidy policies using monthly billing data. We first provide evidence of a lack of bunching in response to the subsidy notches. We then compare the distributions of consumption before and after the introduction of the 400 kWh notch, finding little suggestion that the discontinuity substantially reshaped consumption for residential customers. Then, we consider a hypothesis that is more consistent with the literature on inattention and optimization failures, namely that consumers respond to the notches primarily after they are affected by a price shock from crossing the threshold.

2.4.1 Bunching at Notch Points

Given the magnitude of the effect of these subsidy policies on average prices, consumers might be expected to bunch below the notch thresholds at 100, 200, and 400 kWh (Blinder and Rosen, 1985; Kleven and Waseem, 2013). Figure 2.4 plots the distribution of billed kWh within 50 kWh on either side of the three thresholds during their periods of applicability separately for domestic and informal settlement customers. The figures show no visible evidence of bunching. Manipulation tests at the thresholds using the local polynomial density estimation approach developed in Cattaneo et al. (2019) have t statistics of .026, 1.27, and -.4995 at the 100, 200, and 400 kWh thresholds, respectively.

The lack of bunching in spite of strong incentive to do so would imply exceedingly small elasticities of demand with respect to price. Almost none of the residential consumers served by the utility during this period have a meter that provides real time information on consumption during their current billing period. Most of the meters have display consumption in kWh, but the counter does not reset at the start of new billing period. To precisely target the threshold consumers would need to record the level of the counter at the beginning of each billing cycle. Moreover, due to the slab adjustment described above, the location of the threshold varies slightly for each billing cycle start and end date. For instance, the location of the 400 kWh threshold is approximately equal to the number of days in the billing cycle times 400 divided by 30, the number of days in a typical billing cycle. While a customer on a 30-day billing cycle faces the threshold at approximately 400 kWh, a customer on a 35-day billing cycle faces the threshold at approximately 466.67 kWh (400 divided by 30 times 35).

2.4.2 Imprecise Targeting of the Threshold

Faced with the difficulty of precisely manipulating the threshold, customers who are aware that their consumption is likely to fall near one of the notches may instead shade their consumption to safely avoid facing the price shock. Rather than generating bunching at the thresholds, this response would see consumers in a larger band around the notches locating well below the notch. Depending on the degree of imprecision in customers' beliefs about their consumption, this type of response could generate a significant distortion.

While it is difficult to rigorously test this hypothesis, Figure 2.5 seeks to shed light on whether the introduction of the 400 kWh in August 2015 substantially reshaped the distribution of consumption for residential customers. It plots the distributions of slab-adjusted billed kWh separately for the 12 months before the introduction of the 400 kWh notch for domestic and informal settlement customers in red and the 12 months after in blue. If consumers shade their consumption in response to the notches, we would expect to see additional mass below the threshold after its introduction. The figure shows the opposite: consumption shifts out after the introduction of the subsidy below 400 kWh. This likely reflects a combination of a time trend in consumption growth and increased consumption in response to the subsidy applied to consumption below 400 kWh. While we cannot disentangle these factors, the figure suggests that the introduction of the subsidy does not appear to have significantly reshaped the distribution of consumption around the threshold.

2.4.3 Payment Responses

We use the discontinuities in average prices created by the notches to study short-run elasticities of payment and consumption to prices. To do so, we compare leading consumption and arrears of customers whose billed kWh fall just above and below one the thresholds in the same month. Our regression discontinuity approach estimates these responses separately for the 100, 200, and 400 kWh thresholds during their period of applicability. The remainder of this section describes the empirical strategy in detail, presents the results, and discusses robustness analysis.

Empirical Strategy

While the price schedule creates a sharp discontinuity at the notch points, we use a fuzzy regression discontinuity approach in order to scale the payment and lagged consumption by the magnitude of the price changes. The first stage estimating equation is

$$p_{i,t} = \alpha \mathbf{1}\{e_{i,t} > \bar{e}\} + g(e_{i,t})'\beta + X'_{i,t}\gamma + \sigma_t + \epsilon_{i,t}, \tag{2.1}$$

where $p_{i,t}$ is the average price paid for electricity by customer i in month t; $\mathbf{1}\{e_{i,t} > \bar{e}\}$ is an indicator variable for consumption above one of the price notches at $\bar{e}$; $g(e_{i,t})$ is a local polynomial function of $e_{i,t}$, slab-adjusted billed kWh; $X_{i,t}$ is a vector of customer or bill characteristics, like the sanctioned load of the customer or the length of the billing period; σ_t is a set of year-month fixed effects; and $\epsilon_{i,t}$ is an error. The second stage is then:

$$y_{i,t} = \theta \hat{p}_{i,t} + g(e_{i,t})'\beta + X'_{i,t}\gamma + \sigma_t + \epsilon_{i,t}, \tag{2.2}$$

where $y_{i,t}$ is the payment rate or billed consumption observed on customer i's subsequent bills. The estimation procedure follows Calonico et al. (2014) and Calonico et al. (2019), using MSE-minimizing bandwidth selection and robust inference. We report elasticity estimates for consumption in billed kWh per day and level-log estimates for arrears, which take zero and negative values.

Causal identification in this regression discontinuity design rests on consumers not manipulating the thresholds. Figure 2.4 and the accompanying manipulation tests, which were discussed above, show no evidence of bunching, supporting this assumption. Notably, the form of imprecise targeting of the threshold described in Section 2.4.2 would not violate the RD identification assumptions provided that responses are continuous across the threshold. In the robustness section below we show that covariates and other characteristic are indeed continuous across the thresholds.

Results

We estimate the RDs using the universe of customer bills falling close to the threshold for the period during which each subsidy was in effect for residential customers with loads of 10 KW or less. Figures 2.6, 2.7, and 2.8 present the results graphically and Table 2.3 reports regression estimates. The regressions control for bill year-month fixed effects, a dummy for whether the bill is for an informal settlement customer, and the customer's sanctioned load. The approach to the RD plots follows (Calonico et al., 2015): the outcome is plotted as the mean in disjoint one kWh bins along with a fourth-order polynomial fit separately on each side of the threshold. Figure 2.6 shows the first stage for each notch threshold. The 400 kWh threshold generates the largest average price discontinuity. Above 400.5 kWh, the average price immediately rises by about 50 percent. The discontinuities at 100 and 200 kWh result in price increases of about 31 and 37 percent, respectively.

Figure 2.7 presents the RD plot for consumption on customers' next bill, and Table 2.3 reports estimates for the second and third leading bills as well. There is a clear discontinuity in leading consumption for the 400 kWh threshold, though it is small. Using the fuzzy RD, the implied elasticity of leading bill consumption with respect to the average tariff at the 400 kWh threshold is -.026. Reductions in consumption on the next bill for the 100 and 200 kWh threshold are each about half this size in magnitude and only marginally significant. Across the three thresholds, the consumption responses appear to persist to the third leading bill. In the case of the 100 kWh threshold, the reduction in consumption more than doubles between the first and third bill. In contrast, at the 400 kWh the effect decays by about 36 percent from the first to third leading bills. Across the specifications, the optimal bandwidth varies from 4.7 to 22.4 kWh.

Figure 2.8 shows the RD plot for arrears in INR on the next bill, with positive values reflecting past-due unpaid charges from previous bills. Across the three subsidy notches, arrears on the bill following the one affected by the tariff shock rise significantly.

Robustness

Figure B.1 plots the RDs for the covariates used in the estimation of the consumption and payment effects as well as other billing characteristics. Observable pretreatment covariates and characteristics of customers such as lagged consumption per bill day, the probability of residing in an informal settlement and sanctioned load do not vary discontinuously across any of the three subsidy notches. Unpaid arrears from past bills rises at the 100kWh and

400kWh thresholds.

The evidence presented on the responses of the utility's customers to large discontinuities in the average price schedule suggest a complex interplay between demand elasticities and payment elasticities with respect to prices. Following a price shock, reductions in consumption appear to be small but persistent, while increases in unpaid charges appear to be large but transitory.

2.5 Long Run: Instrumental Variables Estimates of Demand and Payment Elasticities to Average Prices

We turn now to consider the interplay between demand elasticities and payment elasticities with respect to prices in the long run.

2.5.1 Empirical Strategy

Here we describe the instrumental variables strategy we use to estimate price elasticities using aggregated customer-year level data. This empirical strategy takes advantage of minute time series and cross-sectional variation in the electricity price schedule generated by differences in the timing of customers' billing cycles. As described above, because consumers have billing periods of differing lengths, the tariff schedule applies a standardization factor called "slab" to both fixed and variable charges to ensure that consumers face approximately the same price schedule for each unit of consumption. Fixed fees are scaled by the slab, and the ranges of consumption over which the increasing marginal prices of the IBT apply are also scaled by the slab. In effect, a consumer with a 28-day billing period pays approximately 28/30 of the fixed fee of a similar customer with a 30 day billing cycle. For the variable price schedule, the ranges over which each marginal price applies is also scaled by approximately

28/30. In period t, customer i's total charges are

$$\underbrace{s_{i,t} \cdot p^F_{c,t}(w_{i,t}) \cdot w_{i,t}}_{\text{Fixed charges}} + \underbrace{\sum_{j=1}^{J} (\min\{e_{i,t} - \mathcal{E}_{j,c,t} s_{i,t}, (\mathcal{E}_{j,c,t} - \mathcal{E}_{j-1,c,t}) s_{i,t}\})^{+} \cdot p^v_{j,c,t}}_{\text{Variable charges}} . \tag{2.3}$$

The first term describes the fixed charges: $s_{i,t}$ is the slab corresponding to the customer's billing cycle, $p^F_{c,t}(w_{i,t})$ is the per-KW fixed charge facing customers in tariff category c (e.g., residential, commercial, or industrial), and $w_{i,t}$ is the sanctioned load in KW. The fixed charge, $p^F_{c,t}(w_{i,t})$, is represented as a function of load, $w_{i,t}$, because the per-KW fixed charge increases with load.[6] The second term describes the increasing block of the variable charges: $e_{i,t}$ is the quantity in kWh billed in the cycle, the steps in the variable price schedule are located at $(0, \ldots, \mathcal{E}_{j,c,t} s_{i,t}, \ldots, \mathcal{E}_{J,c,t} s_{i,t})$, and $p^v_{j,c,t}$ is the marginal variable tariff on step j. The locations of the steps are scaled by the slab, $s_{i,t}$, and therefore they vary with the dates of the customer's billing cycle.

However, slab is not simply the number of days in each billing period. Instead, the slab formula weights the days in the billing cycle by the total number of days in the calendar month of each billing day. For instance, billing days in March are weighted by 1/31, and billing days in April are weighted by 1/30. To be specific, slab is calculated as

$$s_{i,t} = \sum_{m \in \mathcal{M}_{i,t}} \frac{\text{Bill days in month } m}{\text{Days in month } m}, \tag{2.4}$$

where $\mathcal{M}_{i,t}$ is the set of calendar months with at least one billing day in the billing cycle of customer i on bill t. As a result of weighting bill days by the number of days in each month, billing cycles, which are 30 days at the median, of the same length but starting on different days almost always have different slabs. As a consequence, customers of the same tariff category, sanctioned load, and number of days in their billing face a slightly different price schedule, even if their billing cycles are only offset by a single day.

Billing cycles are heterogeneous in the dataset. In 2018, there were about 40,000 unique

[6] Fixed charges increase with load but are not an IBT. Customers are charged a single per-KW fixed charge based on their sanctioned load.

bill start date and end date combinations among the approximately 1.1 million domestic customers. For an individual customer, billing cycles vary in length in due to the fact that meters are mostly read manually. In order to measure the quantity consumed in each billing period, meter readers go to each connection each month and electronically record the cumulative consumption in kWh on the meter. The previous billing period ends and the new billing period begins at the point at which the recording is taken. As a result, a variety of factors, including weather, holidays, and the season, can generate variation in the billing periods. Variation in billing period lengths may be correlated with unobservable determinants of demand and non-payment. For example, households in some informal settlement areas may be more difficult for meter readers to access. Billing periods in these areas may skew longer and have higher variance, and these areas may also have lower levels of economic formality and quality of public services in general.

Because billing period length is likely confounded, the instrumental variable for average price we construct from the slab adjustment exploits the timing of billing cycles but not the length. The instrument, which we denote below by $z_{i,t}$, is the slab units per billing day. The variation captured by the slab per billing day is that described above, between customers with billing periods of the same length but offset so as to weight differently by the proportion of the billing period falling in different calendar months. We conduct the analysis at the customer-year level, and so we aggregate slab per bill day by summing the slab across each customer's bills in the year and dividing by the number of billing days in the year. At the annual level, the variation in slab per bill day comes from the pattern of billing periods in the year and the particular way in each each cycle falls within calendar months.

It is unlikely that customers optimize consumption with full information about the precise variations in the tariff structure generated by differences in the slab per bill day. In fact, doing so may not even be possible because, as described above, the end date of each billing cycle is subject to some uncertainty. Instead, the more likely mechanism through which these small variations in pricing affect consumption is through experience. In the analysis of responses to the large discontinuities in the price schedule above, we see little contemporaneous response to large changes in the price schedule. However, we show strong evidence that both payments and consumption respond to after experiencing a tariff shock. We hypothesize a similar process operating at the annual level. Variation in the slab per bill day generates minute differences in the average tariff schedule and therefore in the total cost on each level of consumption. Throughout the year, consumers learn about the average price schedule when they receive their monthly bill, and perhaps update their expectations about the cost of the next month's consumption accordingly.

The complexity of the slab per bill day calculation and its small effect on average prices for an individual consumer supports the critical assumption for causal identification that it is exogenous to unobserved determinants of demand and payments. To support this assumption further, we report in Table 2.4 separate univariate regressions of slab per bill day on customer demographics from the survey at the respondent-year level with standard errors clustered at the customer level. These demographics, which include the installed wattage of appliances at the time of the survey, whether the respondent owns their home, the number of rooms in the house, whether the household runs a business from their home, the education of the household head, and whether the respondent lives in an informal settlement, primarily reflect the income of the household the intensity of electricity use. However, the business and informal settlement indicators likely also correlate with the level of formality of the area and perhaps quality of other public services. Among the six specifications, the largest t statistic in magnitude is -1.54 for runs a business from the dwelling. Throughout the IV analysis, we include customer and year fixed effects and a set of billing period characteristics like the number of billing days in the year, the maximum and minimum billing periods lengths during the year, and indicators for having gaps in billing periods or extended billing periods due to the inability of meter readers to access the meter or a broken meter. We also trim the estimating sample to eliminate customer-years with unusual billing cycle patterns that may indicate a disconnection or refusal to allow the meter reader to access the meter.

The first stage regresses the average price on the slab per billing day, controlling for billing period characteristics and customer and year fixed effects:

$$p_{i,y} = \alpha z_{i,y} + X'\beta + \gamma_i + \gamma_y + \varepsilon_{i,y}, \tag{2.5}$$

where $p_{i,y}$ is the log average price billed to customer i in the utility's fiscal year y (from April to the following March) in INR per kWh, $z_{i,y}$ is the slab per bill day in the year, X is a vector of covariates, γ_i and γ_y are customer and year fixed effects, and $\varepsilon_{i,y}$ is an error. As in the previous section, we construct $p_{i,y}$ as the total charges, both fixed and variable, divided by the number of billed kWh. The second stage regresses the log total billed units in the year on the predicted price from the first stage:

$$e_{i,y} = \sigma \hat{p}_{i,y} + X'\delta + \gamma_i + \gamma_y + \eta_{i,y}, \tag{2.6}$$

where $\eta_{i,y}$ is an error. Throughout the analysis, we cluster standard errors at the customer level.

2.5.2 Results

The richness of the billing dataset enables us explore heterogeneous responses to price variation across residential customer with sanctioned loads of five KW or less from 2015 to 2018. We divide the approximately 4.5 million customer-year observations by domestic and informal settlement subcategories and then into deciles of annual consumption and estimate the specification described above separately for each subsample. Customers are assigned to deciles for the duration of the study period based on the distribution of total billed kWh per day in each subcategory in the final year of data, 2018. Estimating elasticities in deciles also aids with the precision of the first stage because the effect of slab per bill day is fairly non-linear. These non-linearities reflect slab per bill day impacting both fixed and variable charges, as well as the discontinuities in the IBT. Slab per bill day has countervailing effects on fixed and variable charges. Fixed charges are increasing in slab per bill day, but the adjustment also pushes out the steps of the marginal tariff schedule, increasing the width of each step.

Figure 2.9 plots the first stage coefficients on slab per bill day for the deciles of 2018 consumption by customer subcategory. Across subcategories and deciles, the effect of slab per bill day in pushing out the marginal tariff steps dominates and the effect is negative. However, in the lower deciles, where fixed charges make up a larger share of the average total bill amount, the magnitude of the effect is smaller. The reduced precision for informal settlement customers is the result of smaller sample sizes; there are about 5.4 times as many domestic customers as informal settlement customers. Tables 2.5 and 2.5 report these estimates along with those for the included controls. Slab per day variation results in modest and highly statistically significant differences in the total charges per unit. The coefficient of -350.6 on slab per bill day in in column 1 of Table 2.5 corresponds to about a 3 percent reduction in the average price for a one standard deviation increase in slab per bill day. The magnitude of this effect rises to a 4.6 percent reduction in the ninth decile. The magnitudes are similar for informal settlement customers, ranging from -2.2 percent in the bottom decile to -3.5 percent in the seventh decile. The first stage is highly significant, with t statistics of greater than six for all subsamples. Tables 2.7 and 2.8 report the first stage coefficients on slab per bill day for the quintiles of 2018 consumption for small industrial and Non-Domestic Low Tension (NDLT) or commercial customers with sanctioned load less than 50kW. Unlike residential and informal settlement customers, industrial and commercial customers do not face a non-linear tariff structure. The rate for fixed changes is the same regardless of the level of sanctioned load and the rate for energy charges is the same regardless of the level of consumption. Fixed charges are set at the same level for commercial and industrial customers, while energy charges are roughly 10% higher for commercial customers relative to industrial customers. With the consumption distribution having a longer tail, particularly for industrial customers, we see that the instrument becomes relatively weak in the top quintile.

Figure 2.10 and Tables 2.9 and 2.10 report the second stage elasticity estimates for domestic and informal settlement customers. Demand is highly elastic to the average price, with elasticities ranging from -.606 to -1.89. Informal settlement customers appear to be significantly less elastic than domestic customers. In both subcategories, the elastiticies are u-shaped across the deciles of consumption. Domestic customers in the top decile have the least elastic demand in that subcategory. For informal settlement customers, the top decile is comparably elastic to the bottom two deciles. Tables 2.11 and 2.12 report the second-stage estimates for industrial and commercial customers. The elasticities for commercial customers range from -1.438 to -1.726 and appear to be u-shaped across the quintiles of consumption, while the elasticities for industrial customers range from -1.267 to -1.987 and appear to increase monotonically with consumption.

The estimated elasticities are large relative to those reported in studies of electricity demand in India, of which there are very few, and in the United States. Mahadevan (2019) finds an elasticity of -.26 for urban residential customers in the state of West Bengal, which has an annual per capita income of USD 1,500, roughly a quarter that of Delhi. Using older survey data from the 1980s and 1990s, Bose and Shukla (1999) and Filippini and Pachauri (2004) find elasticities ranging from -.29 to -.65 for residential customers across India. Studying the United States, Deryugina et al. (2020) finds residential price elasticities of -.08 after six months rising to -.21 after 19 to 24 months in Illinois, while Ito (2014) finds an elasticity of -.09 in the first four months for customers in California. Reiss and White (2005)'s estimate is -.39 for residential customers in California, though the time horizon is not specified.

Figure 2.11 and Tables 2.14 and 2.13 report estimates of the long-run elasticity of non-payment with respect to the average price holding fixed billed consumption among other controls. The coefficients are positive and appear to decrease in magnitude and significance across the deciles of billed consumption. Among informal settlement customers in the bottom decile, a 1 percent increase in the average price increases arrears by INR 2, which implies that doubling the average price would more than double arrears. The elasticities of non-payment are more than three times as large for informal settlement customers relative to domestic customers in the bottom decile. We do not see a significant effect on industrial arrears. The elasticity of arrears with respect to price exhibits an inverse u-shaped pattern along the quintiles of commercial consumption. Doubling the average price would increase commercial arrears by 13 percent among customers in the middle quintile. In general, the estimates of payment elasticities for commercial and industrial customers are less significant and smaller in magnitude as compared to those of residential and informal settlement customers.

Table 2.1: *Customer Annual Summary Statistics for Informal Settlement and Domestic Customers, 2015 to 2018*

	Mean (1)	Std. Dev. (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)
Panel A. Informal Settlement							
Billed kWh per Bill Day	4.34	3.06	0.65	2.18	3.80	5.82	9.78
Mean tariff in year (INR/kWh)	3.66	3.96	2.50	2.89	3.05	3.45	5.43
Total subsidy received in year (INR)	2870.0	1676.0	374	1610	2705.8	3963.2	5894.8
Mean arrears on bills in year (INR)	763.8	3983.1	1.32	45.6	151.2	440.3	2447.8
Mean payment rate (paid/amount payable) in year	0.63	0.74	0.11	0.38	0.65	0.89	1.03
Number of bills in year	10.8	2.10	6	11	11	12	12
Total billing days in year	340.0	66.1	172	347	363	369	383
Bill days on longest billing period in year	33.9	2.35	32	32	33	35	37
Bill days on shortest billing period in year	29.0	3.56	24	28	30	30	33
Slab per bill day (1000s)	32.9	0.087	32.8	32.8	32.9	32.9	32.9
Observations	692,115						
Panel B. Domestic							
Billed kWh per Bill Day	7.42	8.23	1.15	4.05	6.48	9.68	16.8
Mean tariff in year (INR/kWh)	4.49	7.25	2.56	2.99	3.41	4.84	6.68
Total subsidy received in year (INR)	3527.5	1816.6	230	2336	3524	4742	6556.5
Mean arrears on bills in year (INR)	291.3	1623.8	0.75	1.83	55.7	253.3	1357.0
Mean payment rate (paid/amount payable) in year	0.89	1.54	0.30	0.69	0.93	1.02	1.17
Number of bills in year	10.3	2.02	5	10	11	11	12
Total billing days in year	341.5	68.1	164	348	357	379	386
Bill days on longest billing period in year	35.5	2.15	33	35	36	37	38
Bill days on shortest billing period in year	30.6	3.74	26	30	31	33	34
Slab per bill day (1000s)	32.9	0.089	32.8	32.8	32.9	32.9	32.9
Observations	3,766,055						

Table presents summary statistics at the customer-year level separately for informal settlement (Panel A) and domestic customers (Panel B).

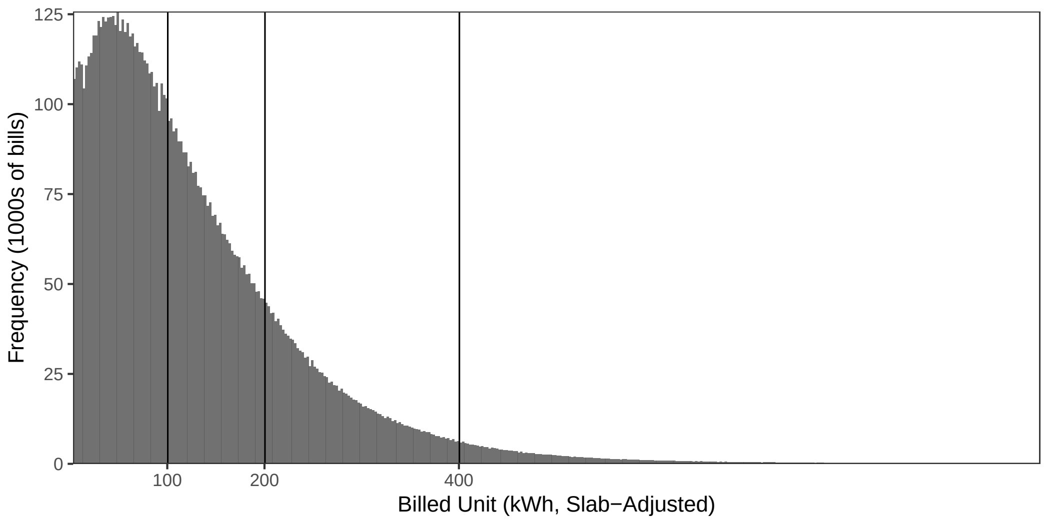
Table 2.2: *Payment Rates and Billed Consumption by Household Characteristics, 2015 to 2018, Survey Sample*

		Payment Rate (1)	Billed kWh (2)
Panel A. Household Characteristics	Mean	Regression Coefficient	
Installed Wattage (KW)	2.775	0.0376***	15.73***
		(0.00326)	(1.445)
Own Dwelling (=1)	0.902	0.0306*	1.911
		(0.0148)	(5.108)
Rooms in Dwelling (=1)	2.283	0.0418***	18.61***
		(0.00362)	(1.348)
Run Business from Dwelling (=1)	0.114	-0.00113	12.42*
		(0.0156)	(4.996)
HH Head Completed Secondary Education (=1)	0.112	0.0683***	17.44***
		(0.0155)	(4.732)
Informal Settlement (=1)	.352	-0.173***	-42.99***
		(0.0109)	(3.292)
Panel B. Annual Household Income (INR)	Share	Mean (Std. Dev.)	
$\leq$ 25,000	0.0056	0.5502	118.87
		(.5045)	(97.73)
[25,000, 50,000)	0.0698	.6461	159.51
		(.4873)	(124.89)
[50,000, 75,000)	0.1869	0.6578	159.94
		(.4860)	(119.33)
[75,000, 150,000)	0.4358	.6780	165.78
		(.4782)	(119.18)
[150,000, 300,000)	0.2292	.7171	185.65
		(.4666)	(128.95)
[300,000, 500,000)	0.0581	.7670	198.414
		(.4420)	(135.37)
[500,000, 1,000,000)	0.0134	.8204	235.98
		(.4136)	(144.76)
$>$ 1,000,000	0.0011	.9066	257.06
		(.3567)	(161.54)
Observations	125,849		

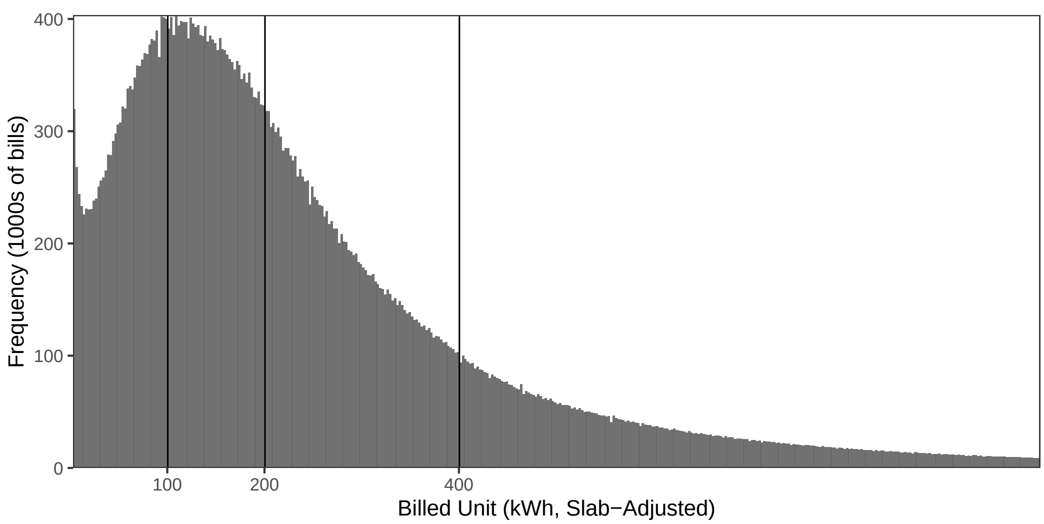
The table presents correlations between household characteristics from the household survey and payment rates and billed consumption from the billing data. In Panel A, columns 1 and 2 report estimated coefficients and customer-clustered standard errors from 12 separate univariate regressions of payment rate and billed kWh, respectively, on the characterisitcs in the rows. In Panel B, the means and standard deviations of these outcomes are reported in each income bin from the survey. * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 2.3: *Distribution of Electricity Consumption, by Customer Category, 2015-2018*

(a) *Informal Settlement*



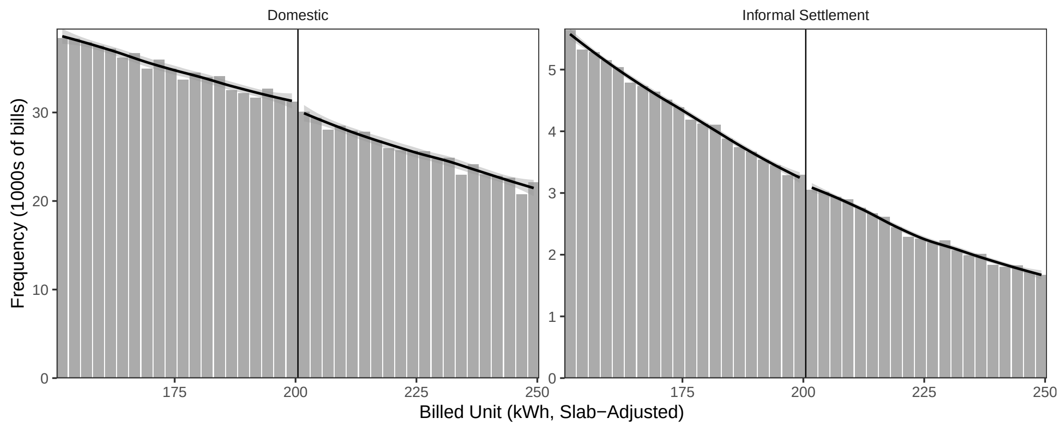
(b) *Domestic*



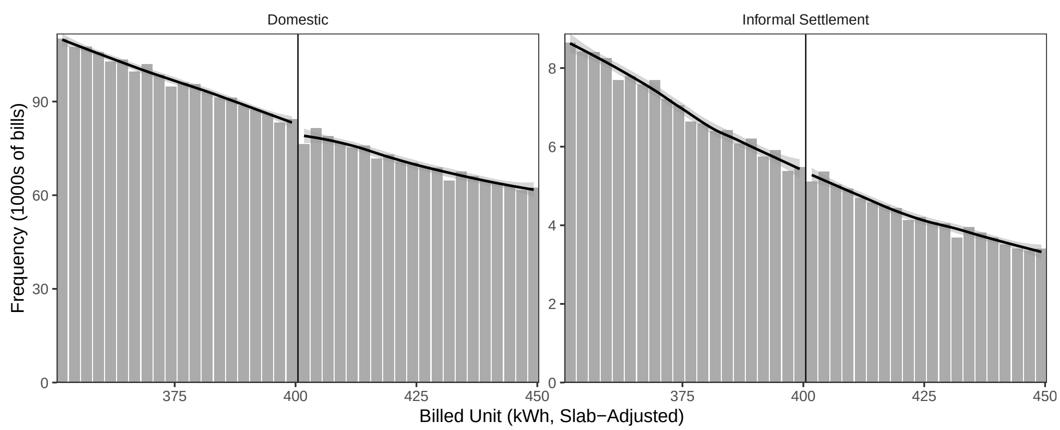
The figures presents the distribution of billed kWh for informal settlement and residential customers during fiscal years 2015 to 2018. The vertical axis represents the number of bills (in 1,000s) in each 2.5 kWh bin. Billed kWh are adjusted by the slab in order to show the location of the notches in the price schedule present at various points during the study period.

Figure 2.4: *Distribution of Billed Consumption Near Price Notches*

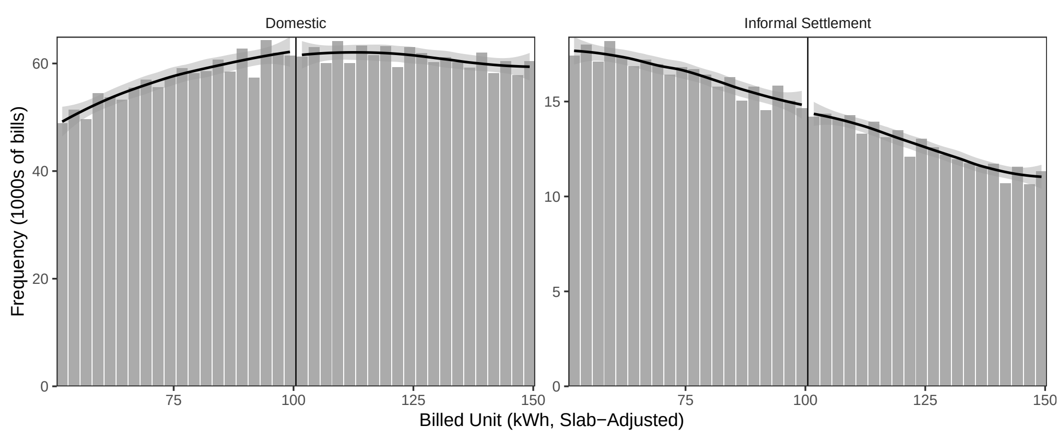
(a) *200 kWh (September 2014 - February 2015)*



(b) *400 kWh (April 2015 - March 2019)*



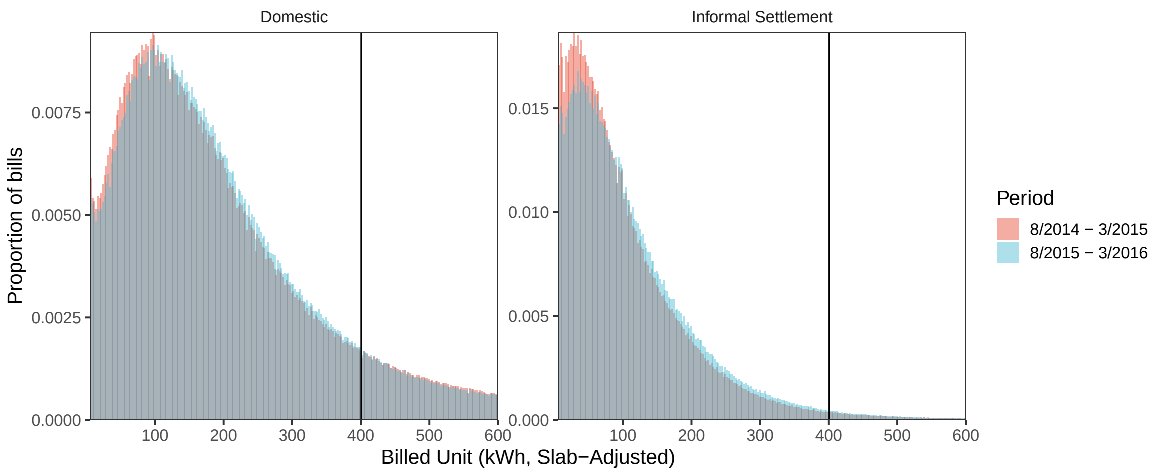
(c) *100 kWh (June 2018 - March 2019)*



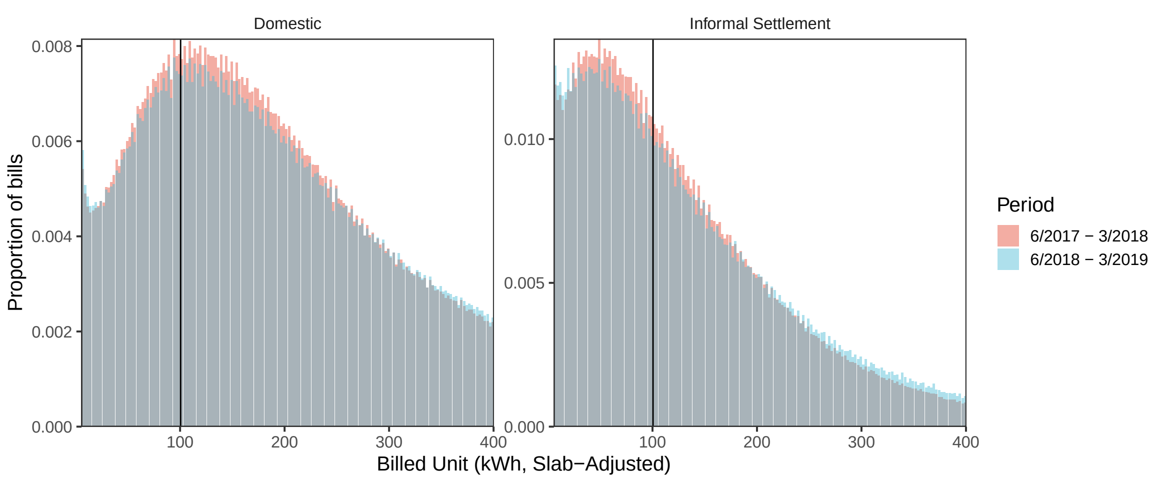
Manipulation tests at the thresholds using the local polynomial density estimation approach developed in Cattaneo et al. (2019) have *t* statistics of .026, 1.27, and -.4995 at the 100, 200, and 400 kWh thresholds, respectively.

Figure 2.5: *Distribution of Billed Consumption Before and After Introduction of 400 kWh and 100 kWh Notches*

(a) *400 kWh (April 2015 - March 2019)*



(b) *100 kWh (June 2018 - March 2019)*



The figure shows the distribution of slab-adjusted billed kWh for domestic and informal settlement customer bills before (red) and after (blue) the introduction of the 400 kWh and 100 kWh subsidy notches. The periods before are chosen to align months of the year, as there is not sufficient coverage in the billing data before (for 400 kWh) or after (for 100 kWh) to plot the full twelve month periods before and after each notch was introduced.

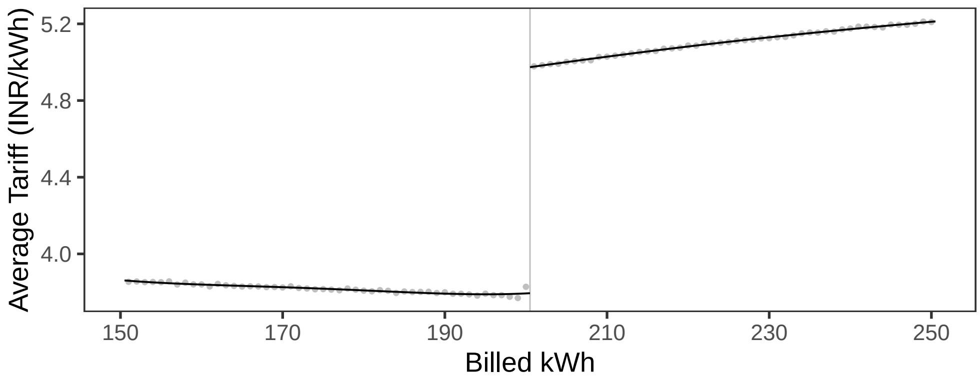
Table 2.3: *Regression Discontinuity Estimates: Short-Run Consumption and Payment Responses to Billing Shocks*

	log Average Tariff (INR/kWh)	Arrears (INR) Lead 1	Arrears (INR) Lead 2	Arrears (INR) Lead 3	log Billed kWh per Day Lead 1	log Billed kWh per Day Lead 2	log Billed kWh per Day Lead 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. 200 kWh (September 2014 - February 2015)							
Above 200.5 kWh (= 1)	0.269***						
	(0.000503)						
log Average Tariff (INR/kWh)		97.25***	-28.37***	-13.43**	-0.0134**	-0.0169**	-0.00611
		(9.024)	(8.343)	(6.709)	(0.00665)	(0.00838)	(0.00899)
Year-Month FEs	✓	✓	✓	✓	✓	✓	✓
Bandwidth (kWh)	6.982	23.46	20.39	26.34	17.68	20.27	22.43
Bandwidth Bias	21.28	35.61	38.17	39.99	32.16	31.99	33.73
Robust p-value		4.71e-19	0.00781	0.0678	0.0732	0.0708	0.404
Observations	2,198,383	2,072,218	2,062,133	1,909,790	1,972,345	1,962,739	1,810,782
Panel B. 400 kWh (April 2015 - March 2019)							
Above 400.5 kWh (= 1)	0.417***						
	(0.00129)						
log Average Tariff (INR/kWh)		148.2***	-36.70***	-0.0981	-0.0264***	-0.0200***	-0.0166***
		(5.946)	(6.028)	(6.044)	(0.00342)	(0.00485)	(0.00625)
Year-Month FEs	✓	✓	✓	✓	✓	✓	✓
Bandwidth (kWh)	1.785	15.74	11.41	9.408	4.762	4.724	4.358
Bandwidth Bias	9.663	23.99	20.84	20.37	25.92	23.69	20.34
Robust p-value		1.25e-91	0.000000112	0.843	1.99e-14	0.0000465	0.00897
Observations	7,995,036	7,577,918	7,515,103	7,389,876	6,811,224	6,768,151	6,597,904
Panel C. 100 kWh (August 2018 - March 2019)							
Above 400.5 kWh (= 1)	0.317***						
	(0.00149)						
log Average Tariff (INR/kWh)		37.94***	8.623**	-3.145	-0.0143*	-0.0205**	-0.0349***
		(3.503)	(3.546)	(3.715)	(0.00778)	(0.00987)	(0.0127)
Year-Month FEs	✓	✓	✓	✓	✓	✓	✓
Bandwidth (kWh)	2.547	12.95	12.02	12.93	7.379	7.947	8.328
Bandwidth Bias	8.286	23.71	20.08	23.04	24.45	23.65	22.65
Robust p-value		2.46e-21	0.0372	0.461	0.0828	0.0467	0.00680
Observations	4,728,325	4,444,317	4,104,822	3,172,676	3,908,689	3,689,500	2,943,920

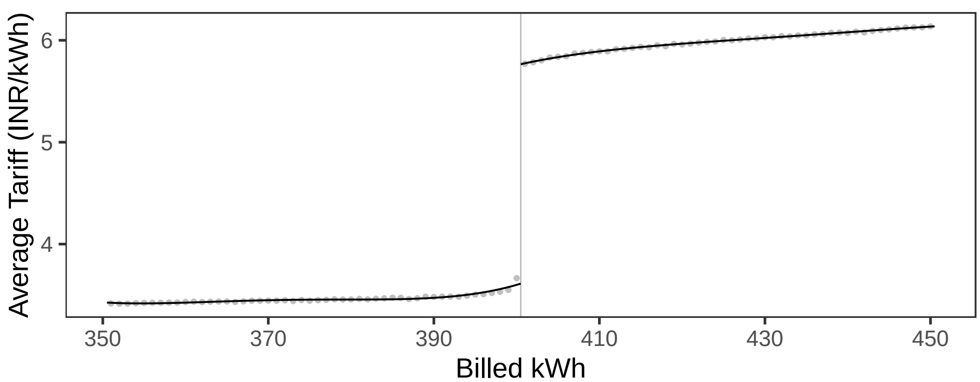
The table presents regression discontinuity estimates using the subsidy notches at 200, 400, and 100 kWh in Panels A, B, and C, respectively. The precise thresholds are at 200.5, 400.5, and 100.5 kWh. The bandwidth selection approach and robust p-values follow Calonico et al. (2014) and Calonico et al. (2019). * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 2.6: *Average Tariff (INR/kWh) on Billed kWh (Slab-Adjusted) Near Subsidy Notches*

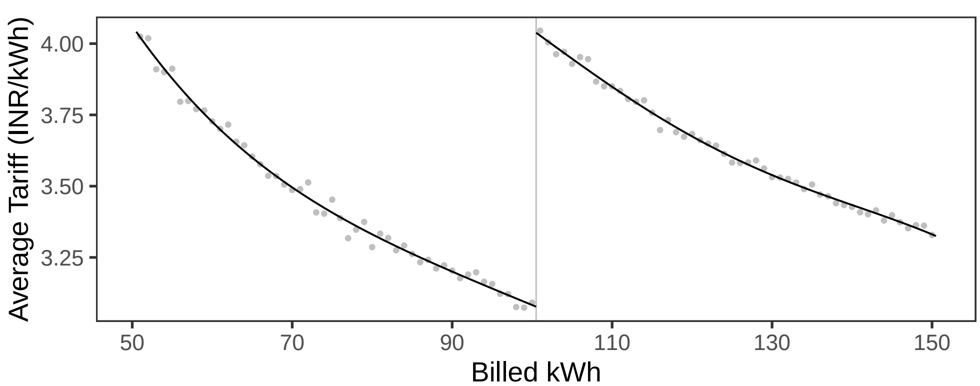
(a) *200 kWh (September 2014 - February 2015)*



(b) *400 kWh (April 2015 - March 2019)*



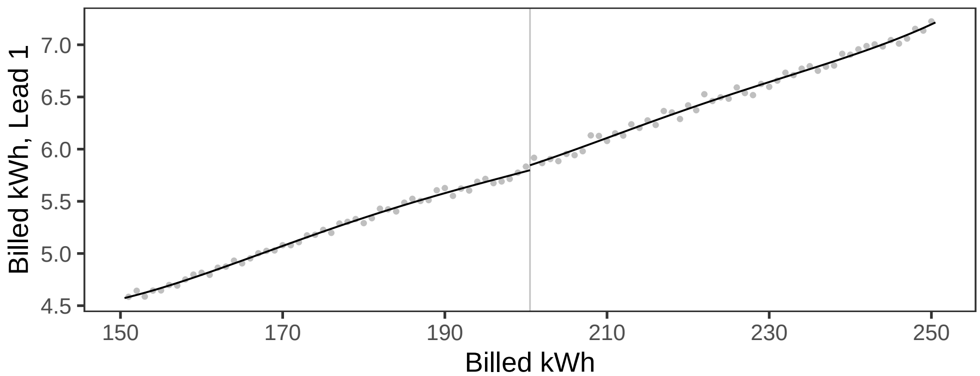
(c) *100 kWh (June 2018 - March 2019)*



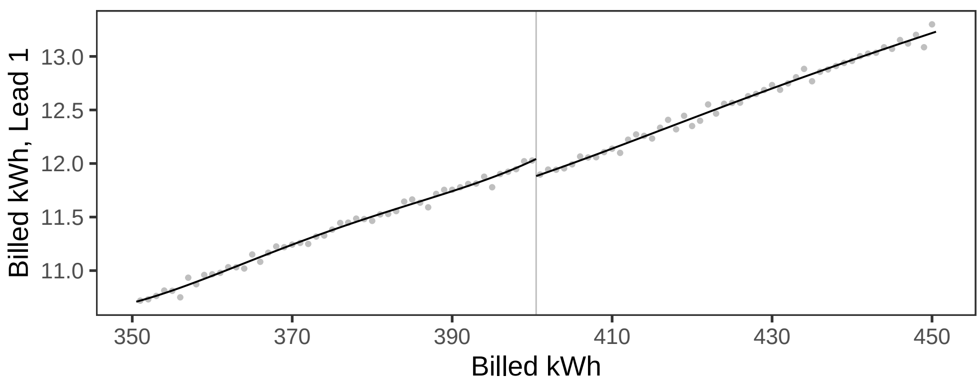
The points represent the mean outcome in disjoint 1 kWh bins. The curves are fourth-order polynomials fit separately on each side of the threshold. The horizontal axis is billed kWh adjusted by the slab. The thresholds are located at 200.5, 400.5, and 100.5 kWh, respectively.

Figure 2.7: *Billed kWh per Day on Next Bill on Billed kWh (Slab-Adjusted) Near Subsidy Notches*

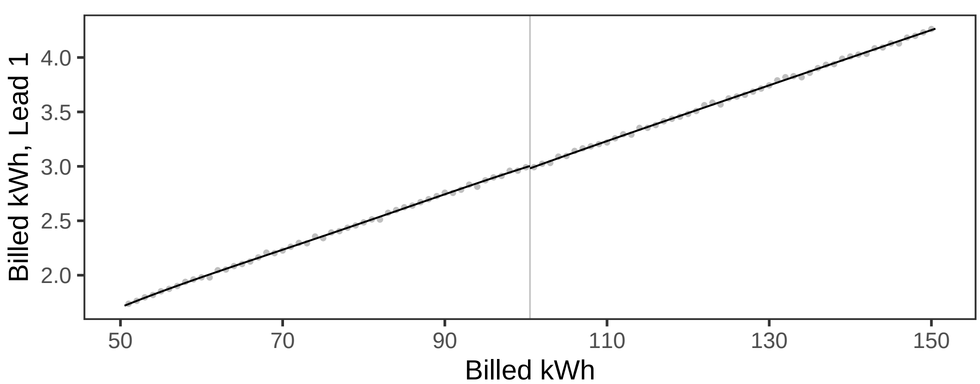
(a) *200 kWh (September 2014 - February 2015)*



(b) *400 kWh (April 2015 - March 2019)*



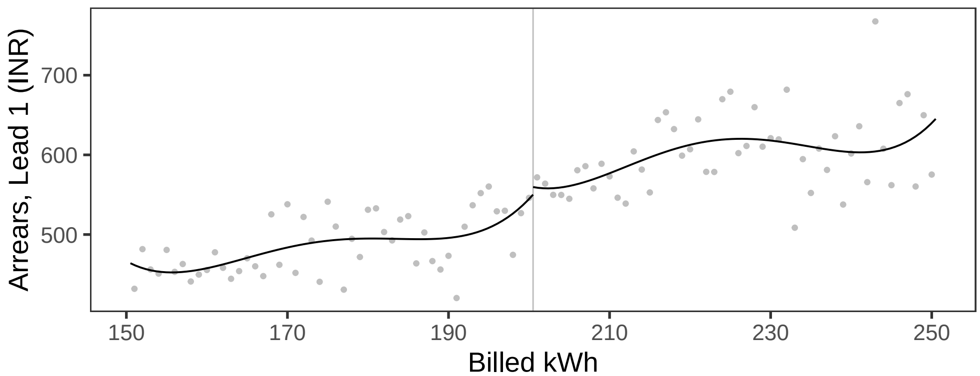
(c) *100 kWh (June 2018 - March 2019)*



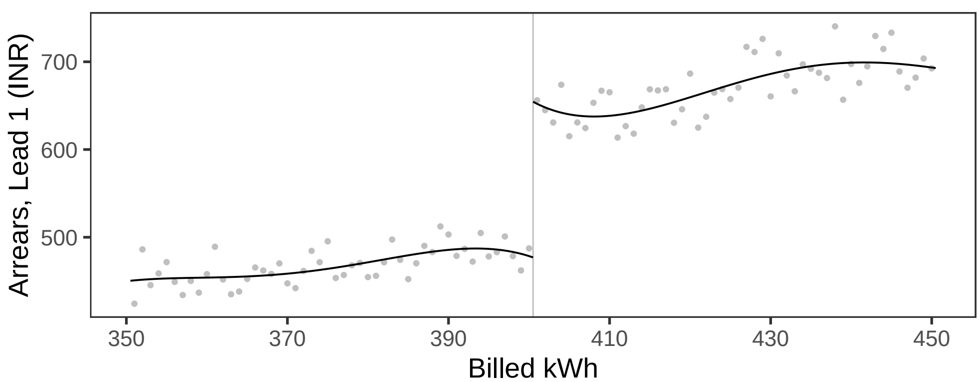
The points represent the mean outcome in disjoint 1 kWh bins. The curves are fourth-order polynomials fit separately on each side of the threshold. The horizontal axis is billed kWh adjusted by the slab. The thresholds are located at 200.5, 400.5, and 100.5 kWh, respectively.

Figure 2.8: *Arrears on Next Bill (INR) on Billed kWh (Slab-Adjusted) Near Subsidy Notches*

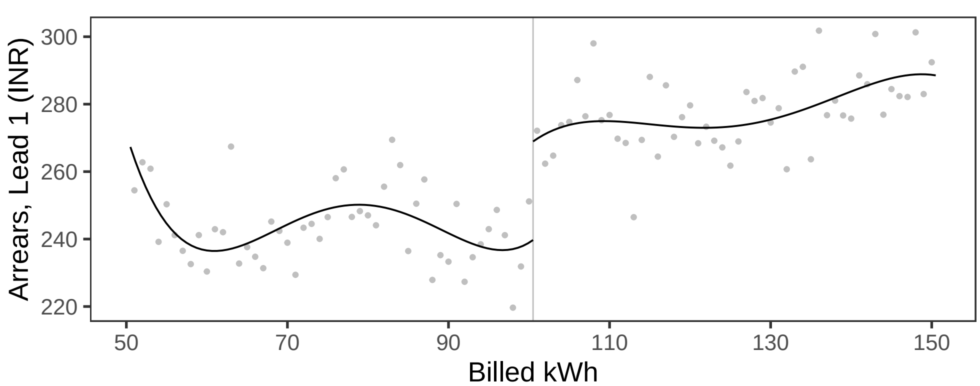
(a) *200 kWh (September 2014 - February 2015)*



(b) *400 kWh (April 2015 - March 2019)*



(c) *100 kWh (June 2018 - March 2019)*



The points represent the mean outcome in disjoint 1 kWh bins. The curves are fourth-order polynomials fit separately on each side of the threshold. The horizontal axis is billed kWh adjusted by the slab. The thresholds are located at 200.5, 400.5, and 100.5 kWh, respectively.

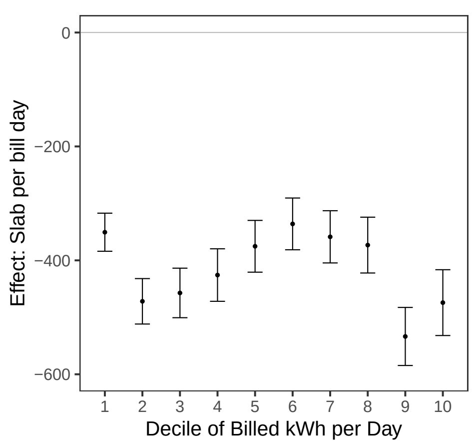
Table 2.4: *Annual Slab per Bill Day on Household Demographics, 2015 to 2018, Survey Sample*

	Slab per Bill Day (1000s)					
	(1)	(2)	(3)	(4)	(5)	(6)
Installed Wattage (KW)	0.000175					
	(0.000252)					
Own Dwelling (=1)		0.00104				
		(0.00165)				
Rooms in Dwelling			0.0000108			
			(0.000339)			
Run Business from Dwelling (=1)				-0.00228		
				(0.00148)		
HH Head Completed Secondary Education (=1)					0.00192	
					(0.00150)	
Informal Settlement (=1)						-0.0000598
						(0.00133)
Constant	32.88***	32.88***	32.88***	32.88***	32.88***	32.88***
	(0.000968)	(0.00156)	(0.00105)	(0.000540)	(0.000542)	(0.000522)
Observations	10545	11488	11487	11493	11336	11505
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	2743	2981	2981	2983	2943	2986
R^2	0.0000203	0.0000166	3.49e-08	0.0000940	0.0000698	0.000000125

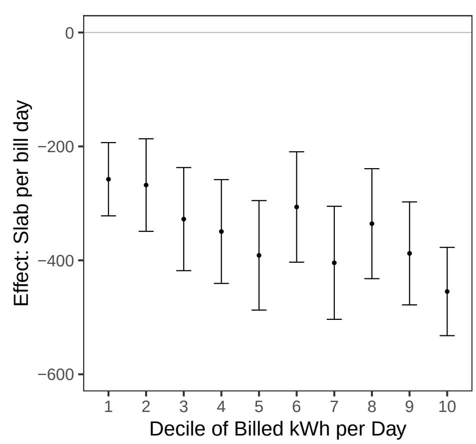
The table report estimates from regressions of slab per bill day in 1000s on characteristics for the survey at the customer-bill level for the sample of customers surveyed. Standard errors are clustered at the customer level. * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 2.9: *First Stage: log Average Tariff (INR/kWh) on Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

(a) *Domestic*



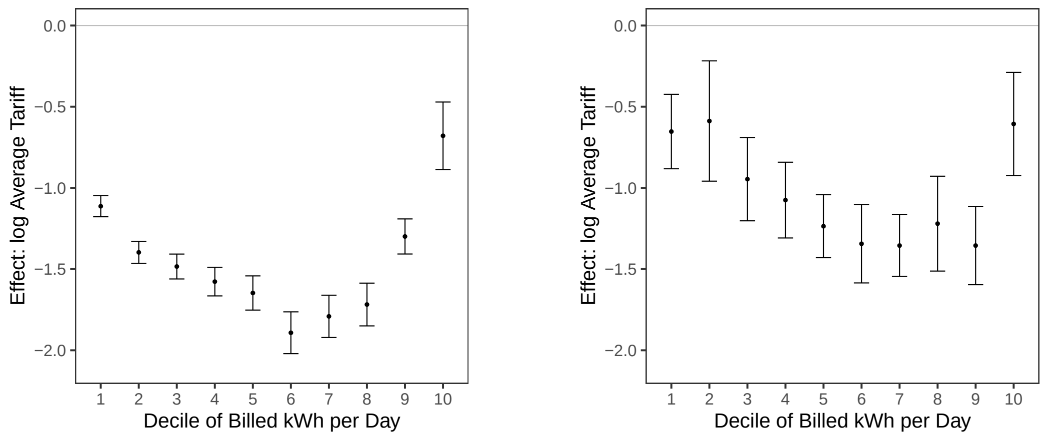
(b) *Informal Settlement*



The figure plots first stage estimates of log average tariff (INR/kWh) on slab per bill day by decile of 2018 billed kWh per day with 95 percent confidence intervals clustered at the customer level. Tables 2.5 and 2.6 present the full specification and additional statistics.

Figure 2.10: *IV: log billed kWh per Day on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

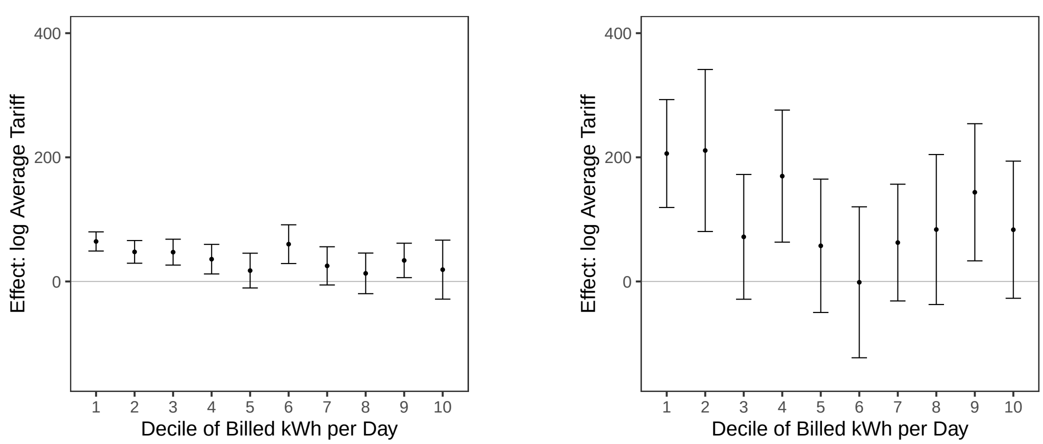
(a) *Domestic* **(b)** *Informal Settlement*



The figure plots IV estimates of log billed kWh per day on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with 95 percent confidence intervals clustered at the customer level. Tables 2.9 and 2.10 present the full specification and additional statistics.

Figure 2.11: *IV: Arrears (INR) on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

(a) *Domestic* **(b)** *Informal Settlement*



The figure plots IV estimates of arrears (INR) on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with 95 percent confidence intervals clustered at the customer level. Tables 2.14 and 2.13 present the full specification and additional statistics.

Table 2.5: *First Stage: Domestic log Average Tariff (INR/kWh) on Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Slab per bill day	-350.6***	-471.9***	-457.2***	-425.8***	-375.3***	-336.0***	-358.7***	-373.2***	-533.6***	-474.2***
	(17.06)	(20.35)	(22.18)	(23.52)	(23.19)	(23.18)	(23.38)	(25.00)	(26.00)	(29.47)
Total billing days in year	-0.00287***	-0.00498***	-0.00390***	-0.00333***	-0.00290***	-0.00231***	-0.00178***	-0.000720***	0.000197	0.00116***
	(0.000267)	(0.000171)	(0.000158)	(0.000160)	(0.000155)	(0.000156)	(0.000163)	(0.000175)	(0.000194)	(0.000253)
Number of bills in year	-0.00576	0.118***	0.0911***	0.0795***	0.0714***	0.0561***	0.0441***	0.0117**	-0.0174***	-0.0443***
	(0.00874)	(0.00515)	(0.00463)	(0.00468)	(0.00449)	(0.00457)	(0.00484)	(0.00522)	(0.00576)	(0.00766)
Bill days on longest billing period in year	-0.000866	-0.00331***	-0.00433***	-0.00464***	-0.00598***	-0.00605***	-0.00590***	-0.00540***	-0.00276***	-0.00345***
	(0.000942)	(0.000758)	(0.000738)	(0.000759)	(0.000747)	(0.000761)	(0.000763)	(0.000824)	(0.000844)	(0.00102)
Bill days on shortest billing period in year	0.0157***	0.0102***	0.00726***	0.00664***	0.00558***	0.00508***	0.00468***	0.00413***	0.00374***	0.00296***
	(0.000581)	(0.000395)	(0.000369)	(0.000361)	(0.000351)	(0.000352)	(0.000356)	(0.000372)	(0.000399)	(0.000505)
Number of days of gap	0.000389***	0.0000888**	0.000297***	0.000353***	0.000260***	0.000376***	0.000293***	0.000286***	0.000232***	0.000107
	(0.0000274)	(0.0000436)	(0.0000538)	(0.0000595)	(0.0000696)	(0.0000609)	(0.0000696)	(0.0000711)	(0.0000690)	(0.0000780)
Number of provisional bills	0.0374	0.0511***	0.0463***	0.0505***	0.0493***	0.0465***	0.0471***	0.0317***	0.0297***	0.0321***
	(0.0247)	(0.00966)	(0.00748)	(0.00674)	(0.00602)	(0.00547)	(0.00545)	(0.00509)	(0.00484)	(0.00589)
Load at end of year (KW)	0.0819***	0.0813***	0.0709***	0.0714***	0.0672***	0.0615***	0.0538***	0.0478***	0.0375***	0.0255***
	(0.00246)	(0.00126)	(0.000994)	(0.000923)	(0.000794)	(0.000737)	(0.000692)	(0.000696)	(0.000655)	(0.000716)
Constant	13.52***	16.89***	16.40***	15.32***	13.69***	12.42***	13.20***	13.77***	19.13***	17.38***
	(0.554)	(0.660)	(0.721)	(0.765)	(0.756)	(0.756)	(0.763)	(0.815)	(0.848)	(0.960)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean kWh per Day	2.262	3.380	4.283	5.121	5.992	6.946	8.080	9.620	12.22	17.82
Observations	248164	302794	343661	365064	388280	405144	415100	411967	382239	222920
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	75715	88768	98850	103809	109525	113679	115952	115073	106776	63531
R^2	0.722	0.656	0.667	0.669	0.657	0.637	0.619	0.615	0.595	0.575

The table reports first stage estimates of log average tariff (INR/kWh) on slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for domestic customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.6: *First Stage: Informal Settlement log Average Tariff (INR/kWh) on Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Slab per bill day	-257.6***	-267.8***	-327.6***	-349.4***	-391.2***	-306.3***	-404.3***	-335.6***	-387.8***	-454.7***
	(32.80)	(41.45)	(46.17)	(46.49)	(49.04)	(49.44)	(50.63)	(49.24)	(46.12)	(39.53)
Total billing days in year	-0.00773***	-0.00282***	-0.00269***	-0.00161***	-0.00169***	-0.00169***	-0.00157***	-0.00174***	-0.00178***	-0.00163***
	(0.000489)	(0.000244)	(0.000218)	(0.000184)	(0.000202)	(0.000195)	(0.000172)	(0.000183)	(0.000167)	(0.000177)
Number of bills in year	0.157***	0.0421***	0.0402***	0.0154***	0.0168***	0.0250***	0.0246***	0.0338***	0.0413***	0.0421***
	(0.0148)	(0.00708)	(0.00592)	(0.00505)	(0.00530)	(0.00503)	(0.00450)	(0.00479)	(0.00435)	(0.00469)
Bill days on longest billing period in year	0.00279	-0.00244*	0.000617	-0.00447***	-0.00542***	-0.00560***	-0.00663***	-0.00573***	-0.00716***	-0.00468***
	(0.00183)	(0.00127)	(0.00117)	(0.00110)	(0.00113)	(0.00111)	(0.00102)	(0.00115)	(0.00101)	(0.00102)
Bill days on shortest billing period in year	0.0157***	0.00625***	0.00707***	0.00392***	0.00402***	0.00364***	0.00364***	0.00412***	0.00388***	0.00561***
	(0.00143)	(0.000841)	(0.000750)	(0.000624)	(0.000645)	(0.000632)	(0.000520)	(0.000558)	(0.000528)	(0.000555)
Number of days of gap	0.000550***	0.000151**	0.000108	0.0000592	0.000190	0.000393***	0.000202	-0.0000706	0.000210	-0.0000664
	(0.0000577)	(0.0000740)	(0.000102)	(0.000119)	(0.000128)	(0.000144)	(0.000153)	(0.000151)	(0.000163)	(0.000134)
Number of provisional bills	0.0525***	-0.0000398	0.000890	-0.00307**	0.000340	0.000874	-0.00228*	0.0000627	0.000680	0.00298*
	(0.00477)	(0.00224)	(0.00169)	(0.00137)	(0.00126)	(0.00121)	(0.00118)	(0.00113)	(0.00126)	(0.00161)
Load at end of year (KW)	-0.00780	0.0124*	0.0210***	0.0231***	0.0226***	0.0310***	0.0459***	0.0470***	0.0444***	0.0401***
	(0.0108)	(0.00639)	(0.00475)	(0.00366)	(0.00295)	(0.00293)	(0.00239)	(0.00206)	(0.00181)	(0.00158)
Constant	10.37***	10.46***	12.18***	13.02***	14.41***	11.51***	14.71***	12.37***	14.12***	16.29***
	(1.072)	(1.355)	(1.509)	(1.530)	(1.611)	(1.620)	(1.665)	(1.621)	(1.520)	(1.298)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean kWh per Day	1.153	1.728	2.262	2.770	3.297	3.856	4.501	5.257	6.312	8.874
Observations	47244	52865	55933	59826	62378	66436	69894	73729	79588	84213
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	14183	15425	16228	17282	17910	18964	19929	20926	22528	24115
R^2	0.723	0.614	0.630	0.634	0.653	0.654	0.655	0.617	0.571	0.652

The table reports first stage estimates of log average tariff (INR/kWh) on slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for informal settlement customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.7: *First Stage: Industrial log Average Tariff (INR/kWh) on Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
Slab per bill day	-598.5***	-499.8**	-564.8**	-675.1***	3.316
	(190.8)	(214.1)	(239.8)	(226.2)	(172.2)
Total billing days in year	0.0183***	0.00721***	0.00406***	0.000257	-0.00125
	(0.00163)	(0.00103)	(0.000854)	(0.000981)	(0.000980)
Number of bills in year	-0.681***	-0.297***	-0.192***	-0.0660**	-0.00494
	(0.0511)	(0.0299)	(0.0251)	(0.0286)	(0.0295)
Bill days on longest billing period in year	-0.0213***	-0.0109**	-0.00846**	-0.00364	-0.00177
	(0.00661)	(0.00496)	(0.00382)	(0.00459)	(0.00392)
Bill days on shortest billing period in year	-0.0148***	-0.00533	-0.00146	0.00106	0.00292
	(0.00471)	(0.00360)	(0.00284)	(0.00286)	(0.00253)
Number of days of gap	0.00175***	0.000479	0.000378	0.000885**	0.000263
	(0.000358)	(0.000439)	(0.000348)	(0.000422)	(0.000487)
Number of provisional bills	-0.237**	-0.126*	0.0415	0.00800	0.0254
	(0.106)	(0.0747)	(0.0403)	(0.0261)	(0.0207)
Load at end of year (KW)	0.00134	-0.000380	-0.00388***	-0.000705	0.00216**
	(0.00483)	(0.00264)	(0.00122)	(0.00118)	(0.000975)
Constant	24.94***	20.50***	22.35***	25.51***	2.788
	(6.201)	(7.041)	(7.835)	(7.498)	(5.646)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0328	0.0329	0.0329	0.0329
Mean kWh per Day	14.63	21.81	32.20	49.42	76.12
Observations	7922	9282	10415	11198	11478
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	2428	2723	3044	3236	3302
R^2	0.791	0.707	0.663	0.601	0.570

The table reports first stage estimates of log average tariff (INR/kWh) on slab per bill day by quintiles of 2018 billed kWh per day with standard errors clustered at the customer level for industrial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.8: *First Stage: Commercial log Average Tariff (INR/kWh) on Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
Slab per bill day	-110.3***	-276.7***	-324.3***	-454.9***	-369.4***
	(25.32)	(37.73)	(43.10)	(44.81)	(47.29)
Total billing days in year	0.000670	-0.00625***	-0.00609***	-0.00494***	-0.00391***
	(0.000651)	(0.000572)	(0.000497)	(0.000483)	(0.000458)
Number of bills in year	-0.139***	0.139***	0.138***	0.102***	0.0748***
	(0.0217)	(0.0188)	(0.0159)	(0.0153)	(0.0143)
Bill days on longest billing period in year	-0.00505**	-0.0000232	-0.00153	-0.00129	-0.00398**
	(0.00206)	(0.00187)	(0.00175)	(0.00180)	(0.00188)
Bill days on shortest billing period in year	0.0138***	0.0128***	0.0123***	0.00929***	0.00588***
	(0.00132)	(0.00122)	(0.00105)	(0.00103)	(0.00101)
Number of days of gap	0.000710***	0.000330***	0.000374***	0.000409***	0.000529***
	(0.0000448)	(0.0000642)	(0.0000750)	(0.0000931)	(0.0000949)
Number of provisional bills	-0.0719*	0.0427**	-0.0151	0.000114	-0.0128
	(0.0399)	(0.0216)	(0.0114)	(0.0146)	(0.0162)
Load at end of year (KW)	-0.00475	0.0207	0.0191*	0.0122	0.0204**
	(0.0114)	(0.0151)	(0.0113)	(0.0139)	(0.00863)
Constant	8.142***	12.46***	13.83***	18.08***	15.30***
	(0.823)	(1.231)	(1.401)	(1.459)	(1.540)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329
Mean kWh per Day	1.244	1.313	1.726	2.381	3.196
Observations	56307	61037	64032	65817	68188
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	17129	18233	18959	19378	19918
R^2	0.796	0.723	0.697	0.675	0.663

The table reports first stage estimates of log average tariff (INR/kWh) on slab per bill day by quintiles of 2018 billed kWh per day with standard errors clustered at the customer level for commercial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.9: *Domestic log Billed kWh per Day on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Mean tariff in year (INR/kWh)	-1.113***	-1.397***	-1.484***	-1.577***	-1.647***	-1.892***	-1.791***	-1.718***	-1.299***	-0.679***
	(0.0331)	(0.0346)	(0.0391)	(0.0449)	(0.0537)	(0.0657)	(0.0665)	(0.0672)	(0.0551)	(0.106)
Total billing days in year	0.00762***	0.00351***	0.00337***	0.00321***	0.00356***	0.00356***	0.00529***	0.00840***	0.0124***	0.0170***
	(0.000224)	(0.000221)	(0.000202)	(0.000206)	(0.000218)	(0.000237)	(0.000244)	(0.000262)	(0.000304)	(0.000578)
Number of bills in year	-0.185***	-0.0623***	-0.0597***	-0.0534***	-0.0625***	-0.0595***	-0.109***	-0.205***	-0.330***	-0.473***
	(0.00714)	(0.00662)	(0.00617)	(0.00641)	(0.00686)	(0.00755)	(0.00800)	(0.00870)	(0.00996)	(0.0186)
Bill days on longest billing period in year	0.0140***	0.0125***	0.0116***	0.0112***	0.0102***	0.00834***	0.0112***	0.0150***	0.0200***	0.0281***
	(0.000752)	(0.000759)	(0.000765)	(0.000810)	(0.000918)	(0.00106)	(0.00107)	(0.00109)	(0.00110)	(0.00199)
Bill days on shortest billing period in year	-0.00146**	0.00295***	0.00459***	0.00473***	0.00527***	0.00632***	0.00464***	0.000861	-0.00294***	-0.00944***
	(0.000740)	(0.000536)	(0.000469)	(0.000480)	(0.000492)	(0.000552)	(0.000557)	(0.000592)	(0.000621)	(0.000985)
Number of days of gap	-0.000560***	-0.000784***	-0.00103***	-0.00113***	-0.00108***	-0.00125***	-0.00155***	-0.00197***	-0.00271***	-0.00267***
	(0.0000220)	(0.0000369)	(0.0000497)	(0.0000601)	(0.0000700)	(0.0000749)	(0.0000783)	(0.0000836)	(0.000108)	(0.000176)
Number of provisional bills	0.0285	0.0933***	0.0704***	0.0781***	0.0657***	0.0756***	0.0622***	0.0598***	0.0481***	0.0577***
	(0.0267)	(0.0192)	(0.0151)	(0.0160)	(0.0142)	(0.0154)	(0.0141)	(0.0144)	(0.0139)	(0.0176)
Load at end of year (KW)	0.188***	0.147***	0.137***	0.135***	0.128***	0.131***	0.109***	0.0916***	0.0540***	0.0201***
	(0.00360)	(0.00342)	(0.00330)	(0.00360)	(0.00391)	(0.00433)	(0.00388)	(0.00355)	(0.00247)	(0.00312)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean Tariff	8.390	3.622	3.344	3.291	3.339	3.489	3.782	4.317	5.129	6.177
Mean kWh per Day	2.262	3.380	4.283	5.121	5.992	6.946	8.080	9.620	12.22	17.82
Observations	248164	302794	343661	365064	388280	405144	415100	411967	382239	222920
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	75715	88768	98850	103809	109525	113679	115952	115073	106776	63531
First Stage F	422.5	537.7	425.0	327.6	262.0	210.0	235.4	222.8	421.2	259.0
R^2	0.707	0.471	0.345	0.185	-0.00265	-0.341	-0.513	-0.573	-0.206	0.122

The table reports IV estimates of log billed kWh per day on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for domestic customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.10: *Informal Settlement log Billed kWh per Day on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Mean tariff in year (INR/kWh)	-0.653***	-0.588***	-0.946***	-1.075***	-1.236***	-1.344***	-1.355***	-1.220***	-1.355***	-0.606***
	(0.117)	(0.189)	(0.131)	(0.119)	(0.0989)	(0.123)	(0.0971)	(0.149)	(0.123)	(0.162)
Total billing days in year	0.00730***	0.00490***	0.00409***	0.00218***	0.00134***	0.000461*	-0.0000385	0.000407	-0.00106***	0.000773**
	(0.00105)	(0.000591)	(0.000381)	(0.000293)	(0.000240)	(0.000250)	(0.000225)	(0.000291)	(0.000267)	(0.000335)
Number of bills in year	-0.153***	-0.0861***	-0.0678***	-0.0118	0.0140**	0.0381***	0.0588***	0.0510***	0.101***	0.0491***
	(0.0252)	(0.0132)	(0.00906)	(0.00812)	(0.00675)	(0.00663)	(0.00647)	(0.00798)	(0.00787)	(0.0102)
Bill days on longest billing period in year	0.00355*	0.00717***	0.00350***	0.00651***	0.00785***	0.00670***	0.00757***	0.00514***	0.0101***	0.0198***
	(0.00200)	(0.00191)	(0.00129)	(0.00156)	(0.00129)	(0.00143)	(0.00141)	(0.00164)	(0.00176)	(0.00227)
Bill days on shortest billing period in year	-0.00486**	-0.00245	-0.00355***	0.00149*	0.00212***	0.00477***	0.00488***	0.00380***	0.00691***	0.00733***
	(0.00240)	(0.00161)	(0.00116)	(0.000885)	(0.000773)	(0.000768)	(0.000707)	(0.000866)	(0.000823)	(0.00118)
Number of days of gap	-0.000692***	-0.000692***	-0.000677***	-0.000522***	-0.000706***	-0.000881***	-0.000648***	-0.00113***	-0.000711***	-0.000795***
	(0.0000787)	(0.000103)	(0.000104)	(0.000122)	(0.000125)	(0.000128)	(0.000225)	(0.000207)	(0.000217)	(0.000275)
Number of provisional bills	-0.0252***	-0.00327	0.00409	0.00415	0.00731**	0.00697**	0.0120***	0.00746**	0.0133***	0.0235***
	(0.00884)	(0.00452)	(0.00367)	(0.00327)	(0.00313)	(0.00296)	(0.00289)	(0.00292)	(0.00318)	(0.00341)
Load at end of year (KW)	0.0404***	0.0409***	0.0201***	0.0302***	0.0248***	0.0315***	0.0456***	0.0288***	0.0279***	-0.00529
	(0.0120)	(0.00940)	(0.00747)	(0.00688)	(0.00585)	(0.00632)	(0.00633)	(0.00841)	(0.00683)	(0.00739)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean Tariff	7.186	3.745	3.376	3.209	3.106	3.030	3.010	3.034	3.156	3.849
Mean kWh per Day	1.153	1.728	2.262	2.770	3.297	3.856	4.501	5.257	6.312	8.874
Observations	47244	52865	55933	59826	62378	66436	69894	73729	79588	84213
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	14183	15425	16228	17282	17910	18964	19929	20926	22528	24115
First Stage F	61.70	41.74	50.37	56.48	63.65	38.38	63.78	46.43	70.73	132.3
R^2	0.611	0.425	0.506	0.480	0.471	0.419	0.332	0.218	0.0134	0.0122

The table reports IV estimates of log billed kWh per day on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for informal settlement customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.11: *Industrial log Billed kWh per Day on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
log Mean tariff in year (INR/kWh)	-1.285***	-1.267***	-1.655***	-1.763***	-1.987***
	(0.0940)	(0.105)	(0.453)	(0.183)	(0.216)
Total billing days in year	0.000471	-0.0000510	0.00151	-0.000640	0.00191*
	(0.00110)	(0.000680)	(0.00115)	(0.00101)	(0.00104)
Number of bills in year	0.0108	0.0516**	-0.00314	0.0556*	-0.0340
	(0.0429)	(0.0246)	(0.0227)	(0.0294)	(0.0370)
Bill days on longest billing period in year	0.00274	0.00178	-0.00402*	0.00378*	-0.00909
	(0.00312)	(0.00203)	(0.00216)	(0.00223)	(0.00583)
Bill days on shortest billing period in year	-0.00139	-0.00306**	-0.00646***	-0.00236	-0.00754***
	(0.00191)	(0.00152)	(0.00247)	(0.00169)	(0.00261)
Number of days of gap	-0.000102	-0.000268*	-0.000261	-0.000441**	-0.0000485
	(0.000157)	(0.000137)	(0.000199)	(0.000193)	(0.000352)
Number of provisional bills	0.157***	-0.0409	-0.0271	-0.0585**	-0.00547
	(0.0601)	(0.0297)	(0.0318)	(0.0227)	(0.0220)
Load at end of year (KW)	0.0233***	0.0170***	0.0130***	0.00903***	0.0102***
	(0.00220)	(0.00155)	(0.000931)	(0.000778)	(0.000642)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329
Mean Tariff	51.94	17.44	14.54	13.26	13.77
Mean kWh per Day	18.51	41.12	96.38	203.5	503.8
Observations	17204	21613	22611	22827	23067
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	5151	6280	6469	6455	6604
First Stage F	19.58	14.33	1.974	11.80	9.666
R^2	0.834	0.723	0.699	0.660	0.647

The table reports IV estimates of log billed kWh per day on log average tariff (INR/kWh) instrumented with slab per bill day by quintile of 2018 billed kWh per day with standard errors clustered at the customer level for industrial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.12: *Commercial log Billed kWh per Day on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
log Mean tariff in year (INR/kWh)	-1.526***	-1.700***	-1.726***	-1.688***	-1.438***
	(0.0529)	(0.0432)	(0.0524)	(0.0559)	(0.0846)
Total billing days in year	0.00480***	0.000788***	0.00212***	0.00265***	-0.00320***
	(0.000308)	(0.000285)	(0.000273)	(0.000244)	(0.000247)
Number of bills in year	-0.164***	-0.0168**	-0.0503***	-0.0552***	0.155***
	(0.0143)	(0.00800)	(0.00784)	(0.00774)	(0.00946)
Bill days on longest billing period in year	-0.00147	0.00141*	0.00182**	0.00461***	0.0125***
	(0.000927)	(0.000735)	(0.000925)	(0.000953)	(0.00120)
Bill days on shortest billing period in year	-0.00353***	0.000688	0.000831	-0.000542	0.00439***
	(0.000678)	(0.000632)	(0.000581)	(0.000588)	(0.000627)
Number of days of gap	0.000151***	-0.000198***	-0.000374***	-0.000460***	-0.000825***
	(0.0000430)	(0.0000331)	(0.0000437)	(0.0000579)	(0.0000982)
Number of provisional bills	-0.0164	0.0113	0.00499	0.0197	0.00209
	(0.0161)	(0.0101)	(0.0147)	(0.0150)	(0.0150)
Load at end of year (KW)	0.111***	0.0930***	0.0603***	0.0514***	0.0277***
	(0.0100)	(0.00956)	(0.00552)	(0.00334)	(0.000931)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329
Mean Tariff	57.89	18.94	15.59	14.23	13.52
Mean kWh per Day	1.280	2.058	3.814	7.940	52.13
Observations	117344	129849	137327	143969	143612
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	35362	38337	40138	42065	42666
First Stage F	95.44	154.0	128.6	138.5	69.13
R^2	0.877	0.823	0.781	0.740	0.645

The table reports IV estimates of log billed kWh per day on log average tariff (INR/kWh) instrumented with slab per bill day by quintile of 2018 billed kWh per day with standard errors clustered at the customer level for commercial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.13: *Informal Settlement Arrears (INR) on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	Decile of Billed kWh per Bill Day									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Mean tariff in year (INR/kWh)	206.1***	211.0***	71.87	169.7***	57.45	-1.324	62.65	83.68	143.7**	83.38
	(44.34)	(66.58)	(51.28)	(54.28)	(54.80)	(62.04)	(47.97)	(61.64)	(56.36)	(56.37)
Total billing days in year	-0.340	-0.539***	-0.497***	-0.0680	-0.296**	-0.485***	-0.190	-0.481***	-0.665***	-0.789***
	(0.274)	(0.169)	(0.147)	(0.124)	(0.125)	(0.137)	(0.127)	(0.140)	(0.143)	(0.168)
Number of bills in year	29.92***	32.64***	29.41***	18.49***	23.84***	29.03***	20.71***	31.70***	39.81***	46.67***
	(6.713)	(4.823)	(4.184)	(3.938)	(3.722)	(3.830)	(3.793)	(3.949)	(4.208)	(4.923)
Bill days on longest billing period in year	2.550***	4.220***	1.760***	2.327***	3.700***	1.905**	1.644**	2.461***	5.073***	3.761***
	(0.716)	(0.723)	(0.650)	(0.798)	(0.779)	(0.768)	(0.810)	(0.812)	(0.921)	(0.961)
Bill days on shortest billing period in year	2.645***	3.046***	2.671***	1.190***	1.512***	1.807***	1.302***	1.645***	1.445***	1.348***
	(0.774)	(0.540)	(0.500)	(0.412)	(0.402)	(0.414)	(0.395)	(0.413)	(0.401)	(0.496)
Number of days of gap	0.0535*	0.145***	0.248***	0.286***	0.202***	0.141**	0.364***	0.208***	0.200**	0.312***
	(0.0276)	(0.0316)	(0.0432)	(0.0547)	(0.0591)	(0.0681)	(0.0720)	(0.0740)	(0.0844)	(0.0768)
Number of provisional bills	-13.73***	-7.249***	-5.666***	-8.278***	-8.945***	-9.700***	-8.552***	-8.008***	-11.54***	-11.36***
	(3.088)	(2.192)	(2.108)	(2.095)	(1.931)	(1.938)	(1.924)	(1.907)	(2.017)	(2.466)
Load at end of year (KW)	15.65***	21.45***	22.95***	25.50***	29.58***	34.35***	28.99***	31.06***	35.60***	34.62***
	(5.023)	(3.912)	(3.640)	(3.438)	(3.233)	(3.314)	(3.420)	(3.904)	(3.607)	(3.529)
Billed kWh per Bill Day	69.99***	57.51***	39.95***	39.53***	30.64***	26.16***	28.76***	24.56***	21.86***	20.36***
	(7.874)	(7.059)	(3.742)	(2.922)	(2.106)	(1.780)	(1.141)	(1.099)	(1.583)	(2.466)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean Tariff	7.039	3.746	3.377	3.211	3.103	3.028	3.002	3.023	3.140	3.725
Mean kWh per Day	1.030	1.664	2.219	2.726	3.253	3.814	4.456	5.205	6.245	8.446
Mean Arrears	187.0	198.8	208.3	215.1	218.1	223.0	231.6	238.1	258.3	314.8
Observations	43332	49324	52397	55699	57827	61399	64143	67253	71471	67843
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	13107	14677	15503	16418	16983	17975	18789	19644	20920	20431
First Stage F	74.52	43.97	65.51	57.11	65.27	38.76	65.12	40.93	59.88	67.65
R^2	-0.112	0.0150	0.0523	0.0366	0.0498	0.0462	0.0524	0.0509	0.0573	0.0699

The table reports IV estimates of average arrears (INR) on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for domestic customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.14: *Domestic Arrears (INR) on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Decile of 2018 Billed kWh per Day*

	Decile of Billed kWh per Bill Day									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Mean tariff in year (INR/kWh)	64.47***	47.65***	47.22***	35.93***	17.52	60.09***	25.13	13.05	33.90**	19.04
	(7.875)	(9.324)	(10.64)	(12.14)	(14.28)	(15.92)	(15.71)	(16.69)	(14.14)	(24.25)
Total billing days in year	0.185***	0.346***	0.278***	0.201***	0.159**	0.246***	0.0505	0.141	0.195*	0.524***
	(0.0557)	(0.0647)	(0.0615)	(0.0649)	(0.0706)	(0.0743)	(0.0801)	(0.0897)	(0.106)	(0.163)
Number of bills in year	2.423	-5.065**	-2.767	-0.484	0.631	-1.255	4.859*	2.367	0.938	-8.103
	(1.947)	(2.027)	(1.940)	(2.060)	(2.232)	(2.354)	(2.574)	(2.929)	(3.524)	(5.453)
Bill days on longest billing period in year	1.821***	1.589***	1.710***	1.353***	1.407***	1.769***	1.544***	1.755***	2.170***	1.942***
	(0.179)	(0.198)	(0.214)	(0.236)	(0.262)	(0.285)	(0.304)	(0.344)	(0.353)	(0.548)
Bill days on shortest billing period in year	-0.0951	0.463***	0.662***	0.594***	0.636***	0.321**	0.702***	0.339*	-0.0199	0.139
	(0.167)	(0.145)	(0.130)	(0.134)	(0.143)	(0.143)	(0.156)	(0.179)	(0.211)	(0.323)
Number of days of gap	0.0163***	0.0503***	0.0353***	0.0484***	0.0546***	0.00503	0.00302	0.0221	-0.0184	0.0231
	(0.00528)	(0.00954)	(0.0123)	(0.0154)	(0.0167)	(0.0187)	(0.0198)	(0.0219)	(0.0238)	(0.0305)
Number of provisional bills	20.55***	12.07***	13.37***	12.06***	11.54***	6.406	15.07***	15.69***	16.16***	20.45**
	(6.286)	(4.679)	(4.427)	(4.446)	(4.437)	(4.263)	(4.367)	(4.932)	(5.937)	(9.560)
Load at end of year (KW)	16.86***	19.57***	21.01***	22.65***	24.89***	24.65***	26.83***	29.42***	29.13***	38.35***
	(0.987)	(0.958)	(0.920)	(0.987)	(1.035)	(1.031)	(0.901)	(0.879)	(0.739)	(1.000)
Billed kWh per Bill Day	13.38***	11.54***	11.17***	10.95***	9.882***	8.642***	9.054***	8.870***	5.777***	2.235***
	(0.709)	(0.368)	(0.273)	(0.260)	(0.324)	(0.468)	(0.581)	(0.698)	(0.544)	(0.535)
Customer FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Slab Days	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329	0.0329
Mean Tariff	8.071	3.602	3.327	3.272	3.317	3.464	3.749	4.274	5.080	6.113
Mean kWh per Day	2.107	3.283	4.208	5.046	5.914	6.856	7.973	9.476	12.00	17.21
Mean Arrears	88.63	101.1	107.1	114.1	119.7	125.6	134.6	145.0	147.0	143.9
Observations	233829	288361	326578	344881	363927	376175	378902	363232	313499	159870
SE Clustering	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer	Customer
Clusters	72366	86071	95710	100158	105116	108396	109331	105889	92949	49385
First Stage F	456.0	526.1	407.1	313.9	250.8	217.3	228.6	214.5	310.7	134.6
R^2	-0.00795	0.0469	0.0490	0.0485	0.0445	0.0458	0.0432	0.0402	0.0321	0.0356

The table reports IV estimates of average arrears (INR) on log average tariff (INR/kWh) instrumented with slab per bill day by decile of 2018 billed kWh per day with standard errors clustered at the customer level for informal settlement customers. * $p < .1$, ** $p < .05$, *** $p < .01$

2.6 Conclusion

Using a variety of empirical approaches, we find that residential customer demand is very inelastic to electricity prices in the short run. Large but transient increases in arrears following the billing shocks suggest that non-payment may play a role in dampening the magnitude of these elasticities. In particular, customers appear to allow arrears to absorb a portion of their increased charges while modestly reducing their consumption in the months following a billing shock. In the long run, however, both demand and non-payment are highly elastic to prices, though there is significant heterogeneity across the distribution of consumption levels.

These findings contribute to our understanding of the infrastructure quality trap and potential policy solutions in two ways. First, large long-run elasticities of demand with respect to price suggest that the distortions in energy consumption that result from generous retail price subsidies are significant. However, domestic and informal settlement customers consuming the least electricity, which our survey shows are also the poorest consumers, have relatively less elastic demand. The magnitudes of the elasticities of bottom-decile domestic and informal settlement customers are about 40 percent and 52 percent lower than those in the respective sixth decile. In Delhi, as in many Indian electricity markets, cross-subsidization between customer categories means these distortions result both from over-consumption by residential customers and under-consumption by industrial and commercial customers. Interestingly, industrial and commercial demand generally appears to be more elastic than residential demand. Second, the non-payment response to price changes exhibited by the bottom deciles of residential customers suggest that broad price increases may have a deleterious side effect of reducing collection. These non-payment responses are concentrated among the poorest residential consumers to whom electricity subsidies are intended to deliver surplus and who exhibit relatively smaller price elasticities. On the other hand, we find only suggestive evidence of at most modest non-payment responses for commercial and industrial customers.

Taken together, these results complicate the proposal to significantly reduce electricity subsidies in settings like Delhi. While reducing subsidies for poor consumers would come at significant cost in terms of reduced surplus for these consumers – who are also the most difficult to reach with other types of transfers – we also expect non-payment to rise in response to price increases, mitigating the improvements to utility finances these increases are intended to support. In contrast, commercial and industrial customers, who pay prices well above the average cost to the utility, are substantially more elastic to retail prices than residential customers. These large elasticities provide a strong rationale for reducing power prices for these customers. In addition to reducing a large distortion to consumption, the behavioral response to this policy would grow the industrial and commercial customer base. Optimal subsidies should take into account both the demand and payment responses to the price.

Table 2.15: *Industrial Arrears (INR) on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
log Mean tariff in year (INR/kWh)	611.8*	-248.5	1267.5	221.1	24297.1
	(325.9)	(943.5)	(838.0)	(701.2)	(75281.9)
Total billing days in year	-10.17*	-4.323	-9.500**	-5.657	20.90
	(5.298)	(6.405)	(4.743)	(4.246)	(96.58)
Number of bills in year	394.6**	153.4	410.9**	246.3*	408.9
	(194.8)	(251.3)	(181.5)	(138.5)	(737.7)
Bill days on longest billing period in year	35.89***	22.43	42.37***	33.48**	104.1
	(11.43)	(15.78)	(16.27)	(13.00)	(266.5)
Bill days on shortest billing period in year	5.650	-17.79*	7.978	-4.355	-55.01
	(8.221)	(9.945)	(10.89)	(9.595)	(143.3)
Number of days of gap	-0.535	0.950	-0.786	-0.856	6.778
	(0.578)	(0.817)	(0.797)	(0.819)	(26.55)
Number of provisional bills	1326.2***	202.8	204.6	11.41	-80.58
	(446.1)	(297.0)	(300.7)	(204.1)	(1723.7)
Load at end of year (KW)	-2.707	4.250	17.47**	27.49***	-85.38
	(10.87)	(9.198)	(7.137)	(7.085)	(349.1)
Billed kWh per Bill Day	4.741*	-2.623	4.501*	0.191	44.30
	(2.615)	(3.026)	(2.663)	(1.745)	(139.8)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329
Mean Tariff	84.42	22.22	19.35	15.67	13.31
Mean kWh per Day	12.28	19.76	30.32	47.43	73.20
Mean Arrears	620.1	873.5	1200.8	1345.0	1484.2
Observations	7794	9143	10191	10730	10556
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	2393	2696	3005	3148	3133
First Stage F	11.38	5.041	6.298	7.301	0.104
R^2	-0.167	0.0151	-0.0757	0.00295	-5.476

The table reports IV estimates of average arrears (INR) on log average tariff (INR/kWh) instrumented with slab per bill day by quintile of 2018 billed kWh per day with standard errors clustered at the customer level for industrial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.16: *Commercial Arrears (INR) on log Average Tariff (INR/kWh) Instrumented with Slab per Bill Day, by Quintile of 2018 Billed kWh per Day*

	Quintile of Billed kWh per Bill Day				
	(1)	(2)	(3)	(4)	(5)
log Mean tariff in year (INR/kWh)	150.1	158.3*	310.6***	99.48*	92.84
	(111.9)	(85.73)	(101.5)	(58.35)	(78.16)
Total billing days in year	1.273***	2.163***	3.303***	1.520***	2.605***
	(0.412)	(0.789)	(0.795)	(0.499)	(0.516)
Number of bills in year	-16.18	-51.74**	-81.79***	-28.31*	-62.18***
	(12.70)	(22.27)	(22.35)	(15.20)	(15.45)
Bill days on longest billing period in year	4.834***	5.616***	3.998***	4.178***	6.696***
	(1.253)	(1.098)	(1.238)	(1.229)	(1.479)
Bill days on shortest billing period in year	-2.151	-2.030	-2.916*	-0.0563	-1.775
	(1.939)	(1.561)	(1.533)	(0.997)	(1.093)
Number of days of gap	-0.0632	-0.0314	-0.0973*	-0.0496	-0.0178
	(0.0834)	(0.0382)	(0.0562)	(0.0512)	(0.0588)
Number of provisional bills	8.075	-45.57***	-15.84	-25.16	-54.69**
	(19.58)	(16.04)	(17.74)	(17.49)	(25.50)
Load at end of year (KW)	56.87***	49.17***	60.40***	64.44***	47.27***
	(9.592)	(15.45)	(11.18)	(9.219)	(9.719)
Billed kWh per Bill Day	13.07*	17.85**	27.91***	6.016	18.81***
	(7.285)	(7.197)	(9.306)	(4.075)	(5.854)
Customer FEs	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓
Mean Slab Days	0.0328	0.0329	0.0329	0.0329	0.0329
Mean Tariff	86.67	27.49	20.21	17.56	16.04
Mean kWh per Day	1.020	1.163	1.616	2.254	3.067
Mean Arrears	206.8	233.2	274.8	315.4	370.1
Observations	54381	59766	62627	64091	65750
SE Clustering	Customer	Customer	Customer	Customer	Customer
Clusters	16590	17899	18645	18994	19417
First Stage F	21.01	42.59	42.72	107.7	62.47
R^2	-0.102	-0.0388	-0.0816	-0.000320	0.0184

The table reports IV estimates of average arrears (INR) on log average tariff (INR/kWh) instrumented with slab per bill day by quintile of 2018 billed kWh per day with standard errors clustered at the customer level for commercial customers. * $p < .1$, ** $p < .05$, *** $p < .01$

Chapter 3

The Long-Run Value of Electricity Reliability in India[1]

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.[2] 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 hours 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

[1]Co-authored with Shefali Khanna

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

utilities engage in short-term non-price rationing of electricity through load shedding, or rolling black-outs (Pargal and Banerjee, 2014). 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. 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.[3] 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 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 distribution utility to provide high quality service. For decade 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, which makes large segments of the customer base loss-making on average. In the case of agriculture, consumption is often unmetered, which prevents utilities from charging

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

a marginal price for electricity and customers from facing an incentive to conserve usage. In response, utilities ration electricity through various means to control their costs. Widespread theft, non-payment of bills and unmetered connections are part of a 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 for decades. In this setting, utility resort to a variety of explicit and implicit forms of non-price rationing of electricity to mitigate their losses.

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 the utility, 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 generates 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. 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 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 4.85 percent.

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 governance of state-owned public service distribution companies. In the remainder of this section, we briefly review these literatures and discuss how our approach complements the existing evidence.

A large literature 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 across several well-identified causal studies in South Africa, Brazil, Ethiopia, India, 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. She uses the land gradient, which 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 show long-run increases in housing values and other development outcomes. Barron and Torero (2016) show positive spillover effects of grid-connected households to non-electrified households in Ethiopia. Together, Dinkelman (2011), Lipscomb et al. (2013), and Barron and Torero (2016) suggest that electrification may be an important driver of increasing productivity and reducing poverty across heterogenous settings.

On the other hand, Burlig and Preonas (2018) and Lee et al. (2020) suggest 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 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 hours 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 here addresses both of these issues by evaluating how residential appliance stocks respond through time to service quality.

The concept of the "value of lost load" (VoLL) in electricity economics, which is the maximum amount a customer is willing to pay to avoid an outage, has been deeply influential in the design of electricity markets, especially in North America and Europe (Hogan, 2013). 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 country settings, power outages are frequent and at least partially predictable, rendering many of the assumptions used to estimate VoLL in developed country settings untenable. However, several recent studies in development economics have sought to use program evaluation methods to evaluate the benefits of electricity reliability, while not estimating VoLL directly.

Chakravorty et al. (2014) and Chakravorty et al. (2016) find that access to electricity leads to large short-run gains in welfare at the village level in India and the Phillippines, respectively. Using micro-data on costs of rural electrification in the Philippines, Chakravorty et al. (2016) predict the evolution of electricity infrastructure over time assuming that proximity to the nearest tapping point in the existing grid is the only factor that determines which villages are electrified first. They then use this measure of predicted electrification as an instrumental variable for the actual electrification status of the village. Chakravorty et al. (2014) uses a similar approach, finding that getting a higher reliability grid connection increased non-agricultural incomes by about 29 percent. Other studies also examine long-term impacts on manufacturing, household consumption, household air quality, and agricultural production (Rud, 2012; Van De Walle et al., 2013; Kitchens and Fishback, 2015).

Dzansi et al. (2018) examine the negative feedback loop between bill payment and load shedding in Ghana, where non-payment contributes to a revenue shortfall for the utility, which in turn may cause the utility to increase load shedding if it is not compensated by the government and therefore cannot procure more power. This phenomenon may trigger a feedback loop where customers reduce bill payment in response to receiving unreliable electricity, either because they low reliability reduces household income and makes them less able to pay their bills or because frequent load shedding reduces customer goodwill towards the utility and erodes the social norm of bill payment. Using household-level data on bill payment and power outages before and after a power crisis in Ghana, they estimate the impact of quasi-random exposure to power outages on subsequent bill payment. In their setting, feeders are given priority primarily based upon critical pieces of government infrastructure on the line such as a hospital, military camp, prison, or defense ministry, which suggests that residential bill payment is not a direct factor in the assignment decision. They find that households quasi-experimentally exposed to rolling blackouts accumulate larger unpaid balances relative to households on essential feeders.

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, particularly in backup capacity, adapt in response to outages.

The evidence presented here aims to complement these studies by exploring the mechanisms through which improved reliability may increase household productivity and analyzing the effects across the distribution of income. As we take this research agenda forward, we also intend to develop market-based estimates of VoLL that are directly comparable to those used in many electricity market regulatory regimes.[4] The approach we use will

[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

combine our reduced form estimates of the long-run effects of outages on consumption and estimates we derive of the price elasticity of demand from the same setting.

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. 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. He shows that the existing subsidies, which provide greater transfers to areas with unreliable supply, deter investment to upgrade infrastructure. Even though the degree of nonpayment in the sample is not known, the possibility of nonpayment raises questions about the interpretation of the demand estimates if bills are not fully enforced. The data does not include the poorest households among whom non-payment is of most concern and nonpayment is not observed in the billing data for the customers studied. Our billing and payments data will enable us to more directly answer the question of how payments respond to reliability. Furthermore, our quasi-experiment will account for the potential endogeneity of outages.

Our analysis is intended to provide direct evidence on the question: could India's electricity distribution utility improve welfare by investing in higher levels of reliability and

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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.

recovering the costs of these investments through higher retail electricity prices?

The paper is organized as follows. Section 3.1 provides background information on the institutional setting of Delhi's electricity distribution segment. Section 3.2 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 3.3 details the empirical strategy we use to estimate the causal effect of reliability on electricity consumption. Section 3.4 presents the results, and Section 3.5 concludes by discussing the policy implications of the findings.

3.1 Delhi's electricity distribution segment

While much of India's electricity distribution segment consists of state-owned distribution-only or integrated generation, transmission, and distribution utilities, several of India's large cities have employed public-private partnership models in distribution (Pargal and Banerjee, 2014). Under these regimes, private companies acquire distribution grid assets and the right to exclusive retail service territories under strict pricing and service quality regulations by an electricity regulatory commission. Generally, these franchising schemes guarantee the franchisee a rate of return conditional on a set of performance criteria related to improving service quality.

Delhi pursued the partial privatization of its electricity distribution system under this model alongside the "unbundling" of the Delhi Vidyut Board, the territory's vertically-integrated, state-owned electricity company, in 2002. The unbundling policy established regulated generation and transmission utilities, an independent system operator called the State Load Dispatch Centre, and a regulatory commission. The distribution segment was divided into five entities, two small legacy distribution utilities serving central government and military areas in central New Delhi, and three public-private distribution franchises. Private operators for the distribution franchises were selected through a competitive bidding mechanisms in which candidate operators bid for five-year aggregate technical and commercial (AT&C) loss reduction targets achievable for a guaranteed rate of return on equity of 16 percent. AT&C losses refer to revenue that is not recovered on energy served due to line losses (technical) and theft and non-payment (commercial).

Figure 3.1 plots AT&C losses of all distribution utilities in India from 2002 until 2016 using data from the Power Finance Corporation's Performance of State Power Utilities Reports. At the time of the partial privatization in 2002, the AT&C losses of the DVB were approximately 50 percent. This is to say that the DVB collected revenue on only about half of the energy it supplied to the distribution grid. While Delhi has few agricultural markets, which are the source of high AT&C losses in many states, it saw exceptionally high rates of theft and bill non-payment. Until the reforms, regulations had prevented the DVB from serving informal settlements that were home to several million people. As a result, these settlements were served exclusively by illegal connections. Over the past 17 years, Delhi's three private distribution franchises have dramatically improved reliability in the capital. According to the Power Finance Corporation, by the mid 2010s the AT&C losses of Delhi's distribution utilities were among the lowest in the country, ranging between 9 and 15 percent (Power Finance Corporation Ltd., 2016).

Figure 3.1: *Annual Aggregate Technical and Commercial Losses in Delhi and Other Distribution Utilities, 2002-2016*

The figure plots the Aggregate Technical and Commercial (AT&C) losses of the utility we worked with in Delhi (green line) and the mean for all distribution utilities in the country (purple line). Each dot in the figure represents a separate distribution utility.

While Delhi's utilities achieved dramatic improvements in service quality and financial performance in the decade and a half following privatization, poor reliability has remained a persistent challenge for customers paying the lowest rates. Between 2007 and 2017, outage durations fell by more than 60 percent for customers in the top two-thirds of average rates. Customers in the bottom third of rates saw only modest improvements in reliability during this period and faced about 2.5 hours of outage on average each month. This gap in reliability between the customers paying the most and those paying the least was a main motivation prompting Delhi's regulators to push outage compensation.

3.2 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 history 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 these two data sources in turn and provides summary statistics for the sample of customers used in estimation.

3.2.1 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, 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 1,100 feeders during the sample period, each of which serves approximately 1,700 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 cannot observe which individual customers are affected by each outage.

3.2.2 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,[5] 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 as part of the survey, enabling us to link their survey responses to their history of electricity bills and outages. At present, approximately 2,800 household are successfully linked to their billing records and approximately 2,000 households are linked to both billing and outage records.

The survey comprised four sections. The first section collected demographic information, including household income, family composition, and basic dwelling characteristics. The

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

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.

3.2.3 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 3.1 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.[6] 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 and appliances, 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.[7]. The overall reduction in contracted load that we observe in 3.1 reflects in part improvements in the efficiency of household appliance stocks. We observe changes in contracted load in about

[6] 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

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

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 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.

Table 3.1: *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).

During the study period, residential customers experienced about 2.64 hours 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 hours 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 by different customer types. Figures 3.3 and 3.4 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 C&I share experienced about half the outage durations of customers on feeders in the bottom quartile. By 2019, this gap had narrowed substantially. Figure 3.4 defines the quartiles by the average price paid for electricity on the feeder. This again reflects the mix of customer types served by the feeder, as C&I customer 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 hours and 20 minutes. 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. Outages broadly improved in the years following 2016.

Figures 3.5 to 3.9 plot responses of the surveyed households to questions concerning their electricity supply. Respondents report nighttime (8pm - midnight) to be 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 all or most of the time respectively. 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, where we randomly varied one of these characteristics across respondents. Figure 3.9 illustrates the responses of households to these 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. The majority of households would prefer a longer anticipated outage to a shorter (i.e. 1-hour) unanticipated outage regardless of whether the duration of the anticipated outage is 2, 3 or 4 hours. 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-hour outage in January to a 1-hour outage in June is larger than the share of households that would prefer a 4-hour outage in January to a 1-hour outage in June, which suggests a marginal effect of the duration of the outage.

Appendix Figure C.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. To understand how much each appliance contributes to the household's total electric bill, one must 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 hours and a hair dryer is used for 5 minutes. The iron consumes 2kWh (1000W x 2 hours) and the hair dryer consumes 0.125kWh (1500W x 0.0833 hours), which implies that using the iron costs roughly 16 times as much as the hair dryer.

Tables C.1 to C.5 summarizes 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. 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 C.2 and C.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 C.5 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.

3.3 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 prices paid by consumers is substantially larger than this. However, because Delhi's utilities are compensated for the subsidy burden, these subsidies should not directly affect their incentives. Figure 3.10 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. Their lower tariff rates reflect lower levels of consumption. 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, distorting the incentive to differential reliability even further. 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 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 potential inability to serve demand. Feeders are also the lowest level of the network at which the utility has comprehensive statistics on reliability.[8] Moreover, the utility generates a priority ranking of feeders according to the average revenue per unit (i.e., the average tariff), which it uses for decisionmaking 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. Figure 3.11 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 instrument we construct, $z_{f,t}$, is the interaction between the proportion of the customers served by each feeder that are commercial or industrial (CI) 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, $p_{c,t} - p_{r,t}$:

$$z_{f,t} = c_{f,2015} \cdot (p_{c,t} - p_{r,t}), \tag{3.1}$$

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

$$c_f = \frac{1}{n_{f,2015}} \sum_{i \in I_f} \mathbf{1}_c, \tag{3.2}$$

[8] Due to the recent rollout of improved 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.

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 CI and residential tariffs, where the average tariffs are defined by:

$$p_{c,t} = \left[\sum_{i=1}^{I} b_{i,t} \cdot \mathbf{1}_c\right] \left[\sum_{i=1}^{I} e_{i,t} \cdot \mathbf{1}_c\right]^{-1}, \quad p_{r,t} = \left[\sum_{i=1}^{I} b_{i,t} \cdot \mathbf{1}_r\right] \left[\sum_{i=1}^{I} e_{i,t} \cdot \mathbf{1}_r\right]^{-1}. \tag{3.3}$$

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

$$o_{i,f,t} = \alpha z_{f,t} + X'\beta + \gamma_i + \gamma_t + \varepsilon_{i,f,t}, \tag{3.4}$$

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 price from the first stage:

$$e_{i,f,t} = \sigma \hat{o}_{i,f,t} + X'\delta + \gamma_i + \gamma_t + \eta_{i,t}. \tag{3.5}$$

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 Figure 3.10, which shows that, particularly for domestic and informal settlement customer, average tariffs vary seasonally as customer 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.

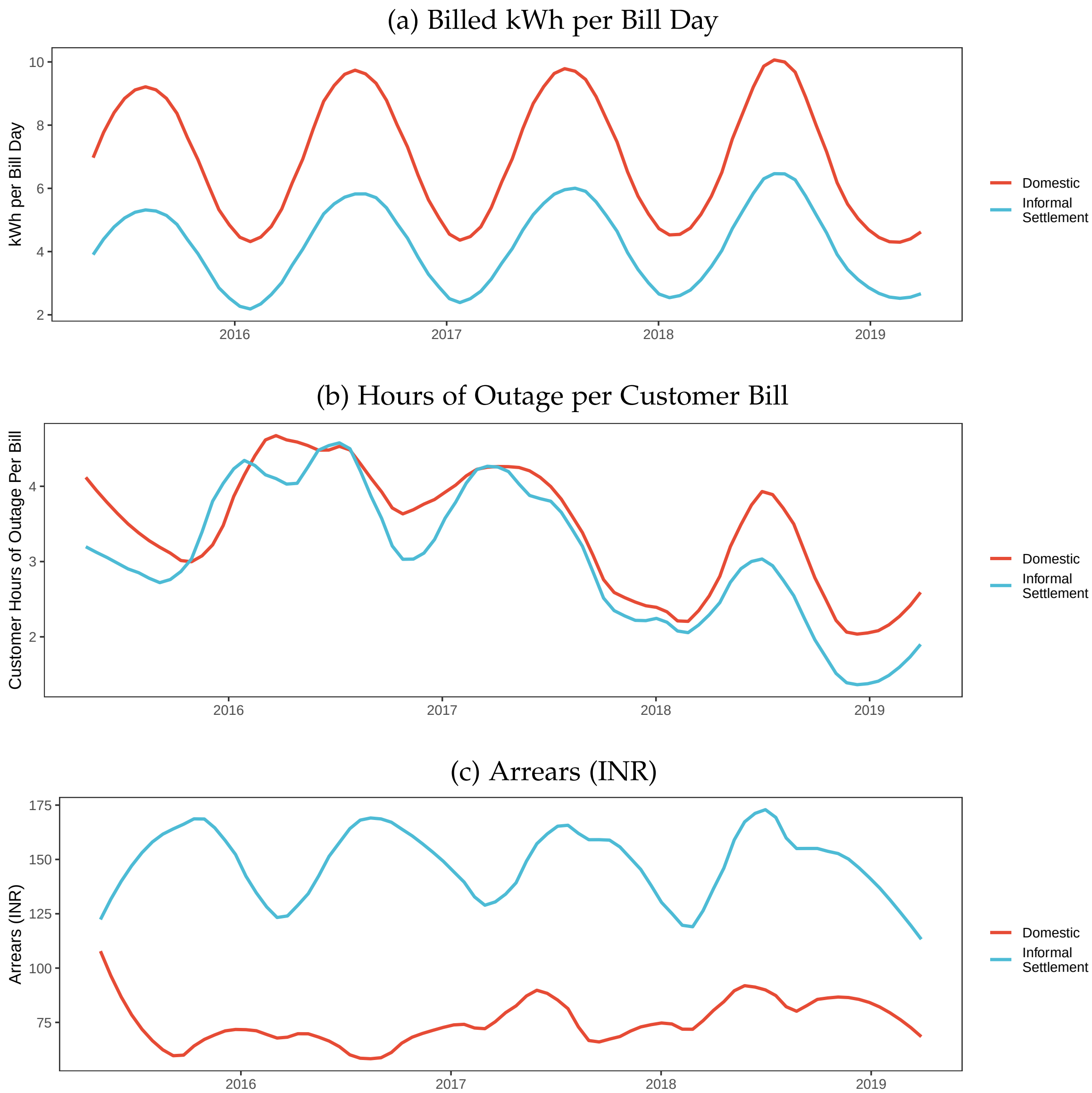
A recent paper by Goldsmith-Pinkham et al. (2020) shows that Bartik instruments are numerically equivalent to using the initial shares as instruments in a Generalized Method of Moments (GMM) weight matrix estimation with the implication that the time-varying component of the instrument only provides the weights and therefore only affects instrument relevance, not endogeneity. Therefore, in our case, the 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. 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 income.

3.4 Results

3.4.1 Main results

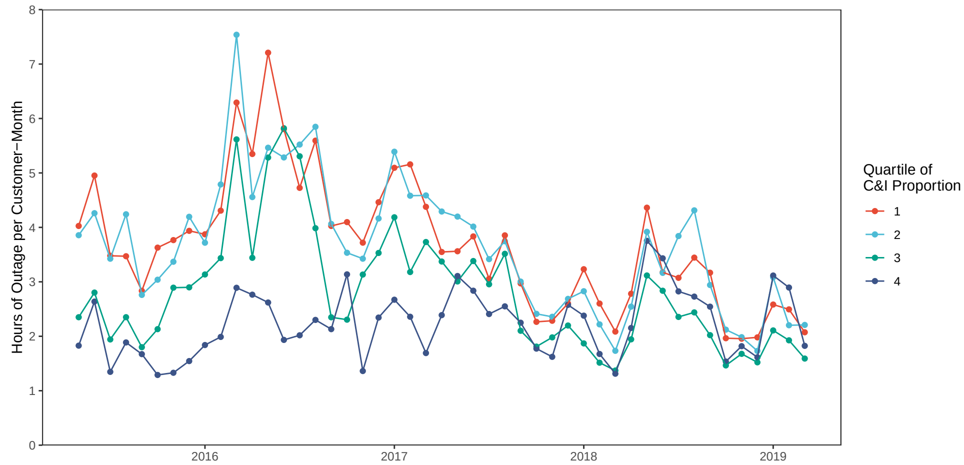
Table 3.2 presents the main estimates of consumption responses to outages at the customer-year level. Columns 1 and 2 report OLS estimates with and without customer and year fixed effects, respectively, column 3 reports the first stage, and column 4 reports the IV estimate. Across the specifications, 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.

Figure 3.2: *Consumption, Outages, and Arrears by Customer Category, 2015–2019*



The figures plot locally 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.

Figure 3.3: *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.

Figure 3.4: *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.

Figure 3.5: *Most common time when outages occur*

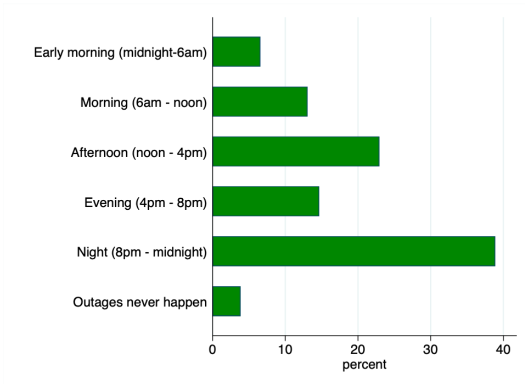


Figure 3.6: *Receive notification before an outage?*

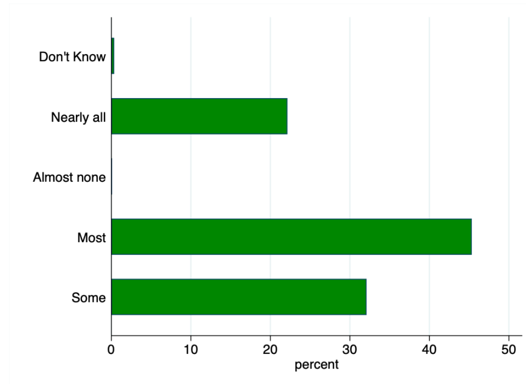


Figure 3.7: *Satisfaction with availability of supply*

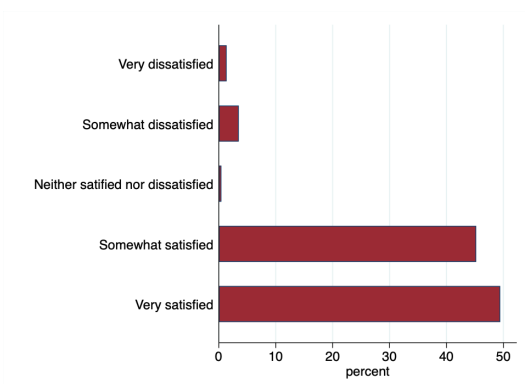


Figure 3.8: *Satisfaction with cost*

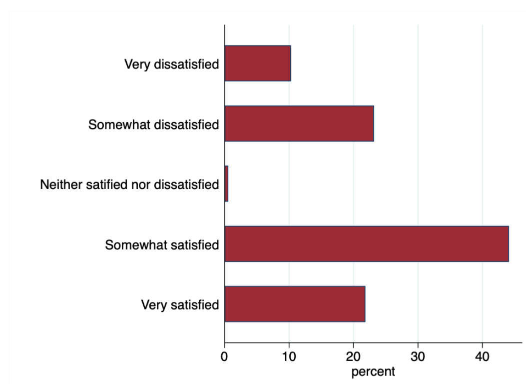
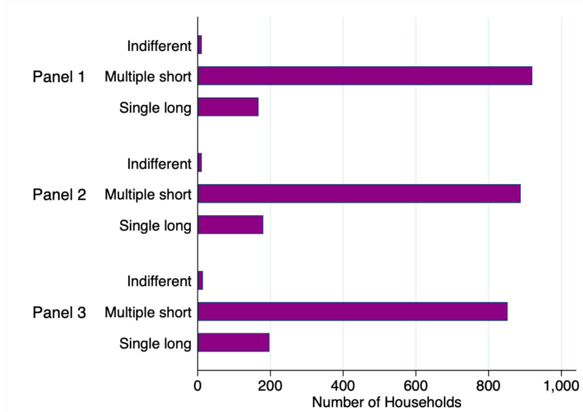
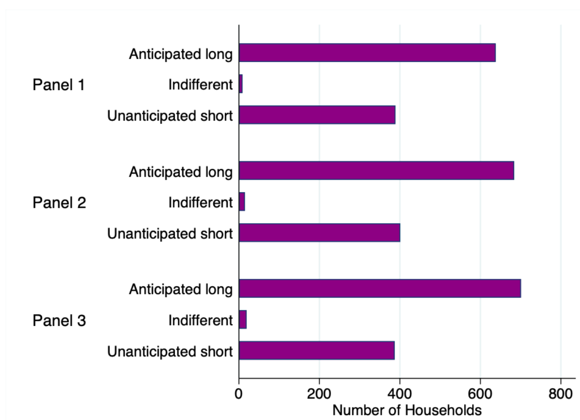


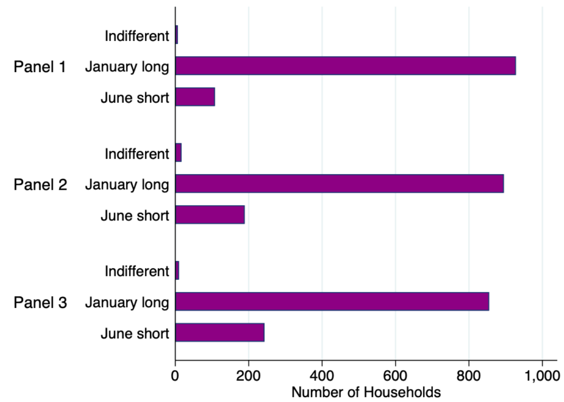
Figure 3.9: *Choice Experiments*



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).

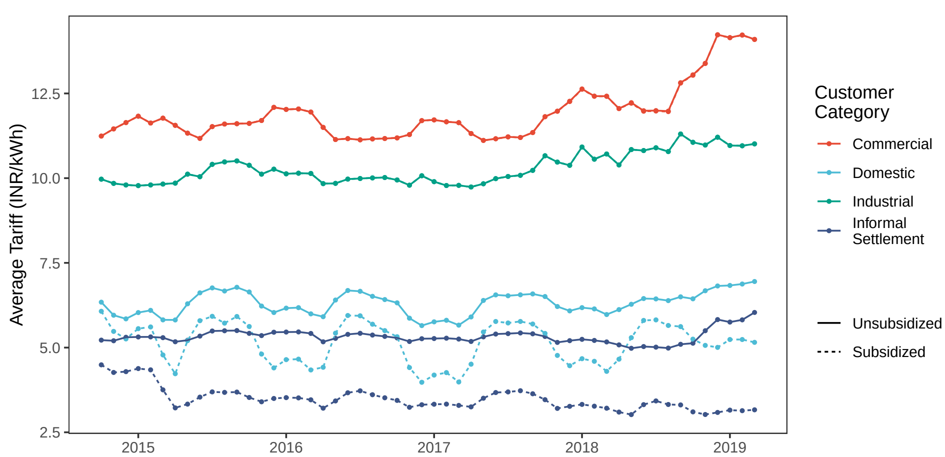


The figure illustrates the responses of three randomly-selected groups of surveyed households that were asked whether they would prefer a 1-hour outage between 6 and 10 pm one night in the next few days with no prior notice or one of the following: a single 2-hour outage between 6 and 10pm one night 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).



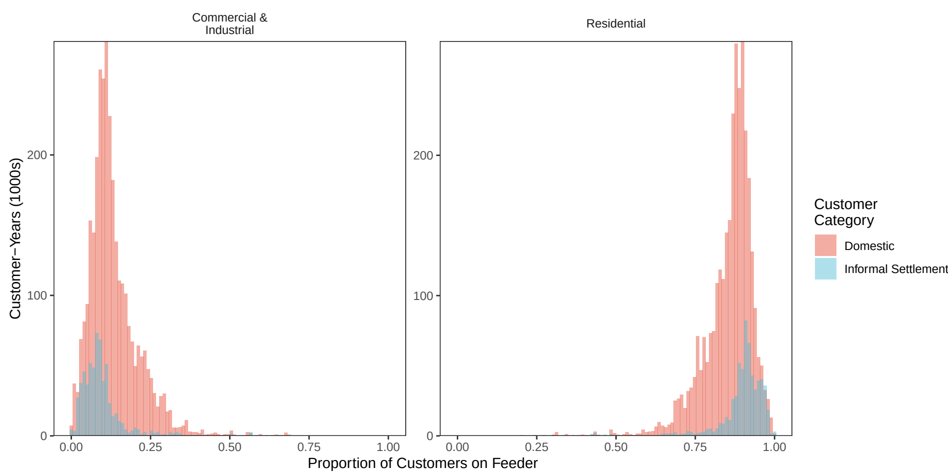
The figure illustrates the responses of three randomly-selected groups of surveyed households that were asked whether they would prefer a 1-hour outage between 6 and 10pm in June or one of the following: a 2-hour outage between 6 and 10pm in January (Panel 1), a 3-hour outage between 6 and 10pm in January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

Figure 3.10: *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.

Figure 3.11: *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.

Table 3.2: *Consumption (log kWh per day) on Hours 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	3350052	3350052	2888276	2799612	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.

Column 3 reports the first stage. The estimated coefficient on the instrument, the annual tariff gap interacted with the feeder's 2015 CI 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 1,100 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 4.85 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 37 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 0.41kW 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 Figure 3.2, these patterns 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 household 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.

3.4.2 Responses of Domestic and Informal Settlement Customers

Tables 3.3 and 3.4 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 that of domestic customers.

Table 3.3: *Domestic Customers: Consumption (log kWh per day) on Hours 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***	-0.00105*		-0.0401***	-0.451***
	(0.00240)	(0.000596)		(0.0112)	(0.121)
CI-residential tariff gap × Proportion CI in 2015			-4.033***		
			(1.111)		
Feeder billed kWh per day	0.00125**	0.0000537	0.0333**	0.00160**	-0.00804
	(0.000567)	(0.000148)	(0.0138)	(0.000749)	(0.00645)
Mean tariff in year on feeder (INR/kWh)	0.0800***	0.0333***	-0.109	0.0227*	0.373**
	(0.00784)	(0.00449)	(0.313)	(0.0132)	(0.154)
Bills on feeder in year (1000s)	-3.084***	1.403***	-24.09	0.345	-0.222
	(0.521)	(0.198)	(22.94)	(0.963)	(10.21)
Mean tariff in year (INR/kWh)	-0.0118***	-0.0134***	0.00148***	-0.0135***	-0.000809***
	(0.000559)	(0.000826)	(0.000376)	(0.000888)	(0.000293)
Bill days in Q1	0.000468***	-0.000986***	0.0105***	-0.000359	0.00282
	(0.0000867)	(0.0000319)	(0.00369)	(0.000222)	(0.00225)
Bill days in Q2	0.00535***	0.00374***	0.00366	0.00369***	-0.0113***
	(0.000137)	(0.0000692)	(0.00324)	(0.000134)	(0.00134)
Bill days in Q3	0.00528***	0.00580***	0.000827	0.00599***	0.00821***
	(0.000155)	(0.000109)	(0.00284)	(0.000163)	(0.00128)
Bill days in Q4	0.0180***	0.00874***	-0.00534***	0.00843***	-0.00287***
	(0.000269)	(0.000160)	(0.00155)	(0.000195)	(0.00103)
Constant	-1.063***	0.120***	5.667***		
	(0.0653)	(0.0321)	(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	2805221	2805221	2401057	2324818	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.

Table 3.4: *Informal Settlement Customers: Consumption (log kWh per day) on Hours 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	544831	544831	487219	474670	408551
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.

A portion of this difference is likely explained by the short-run channel. Informal settlement customers may lose more consumption to 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 conditions 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 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. [9] 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,

[9] Oftentimes, backups such as diesel generators and battery inverters are shared among multiple households in a community, 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.

as the battery enables users to charge the battery 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.

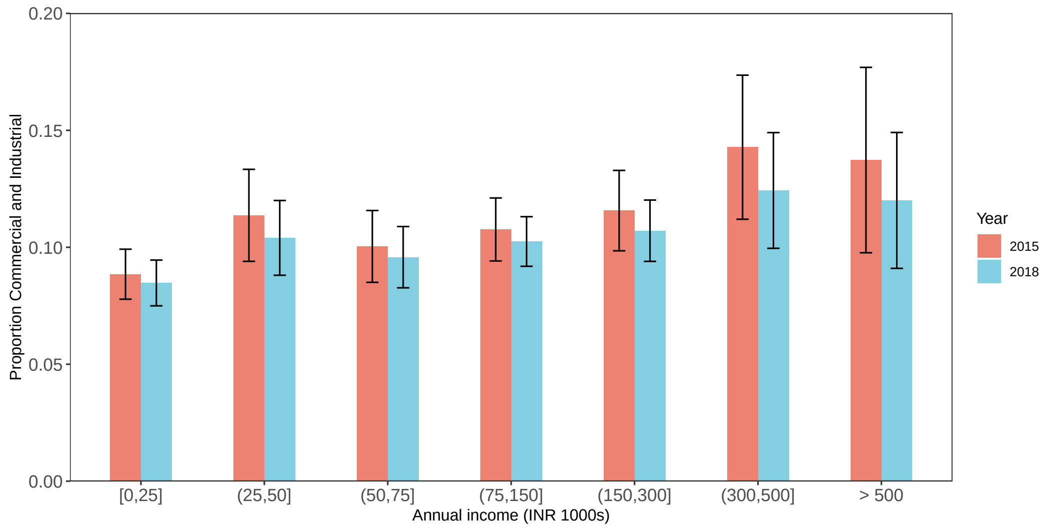
3.4.3 Instrument validity and robustness

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 CI shares. Figure 3.12 plots predicted values and standard errors from two separate regressions of the 2015 and 2018 CI share of each feeder's customer base on income bins for surveyed customers. Table 3.5 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 5) and the average tariff (Column 6), 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.

3.5 Conclusion

In this paper, we find that an additional hour of outage per month reduces annual electricity consumption by 4.85%. These estimates have important implications for the ongoing policy debate on electricity reliability in India. In September 2017, the DERC required that the city's regulated electricity distribution utilities pay compensation to customers experiencing

Figure 3.12: *Proportion Commercial and Industrial in Financial Years 2015 and 2018, by Annual 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.

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. Figure 3.13 shows that reliability improved most among lower paying residential customers following the implementation of the 2017 policy. The improvements were greatest in areas with more informal settlement customers, who are generally very poor. While this policy helped deliver higher reliability primarily to poor consumers, without cost data we are unable to evaluate the efficiency of this policy.

Which such policies would likely induce utilities to reprioritize investments and maintenance decisions, the financial implications for utilities that are already burdened with

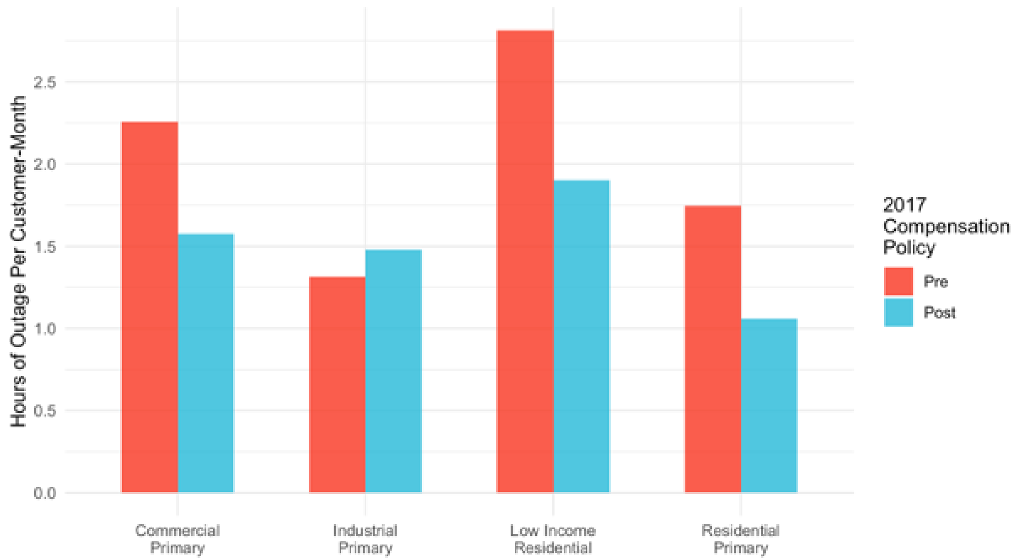
Table 3.5: *Customer and Feeder Characteristics on Income, Surveyed Customers, 2015–2019*

	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.

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 on optimizing rate design and subsidy policies. Cross-subsidized retail tariffs are often 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

Figure 3.13: *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.

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 24 x 7 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 in order to be able 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 utilities optimize their power procurement decisions. Finally, non-payment serves as an additional tax to the extent that the unrecovered costs from commercial losses are rolled into retail tariffs, which suggests that understanding the payment response to long-term improvements in electricity reliability could also go a long way to inform tariff design. Going forward, we plan to estimate the heterogeneous effects of outages by season and customer type as well as the short and long-run elasticity of payments with respect to outages.

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Appendix A

Appendix to Chapter 1

A.1 Wholesale Market Cost Model

The analysis of load shedding presented in Section **??** uses marginal cost estimates from a simple model of wholesale market energy purchase by MSEDCL. The model is intended to provide a consistent framework for estimating the variable contracted tariff of the marginal generator facing MSEDCL in each hour, based on the energy purchase contracts it holds as well as generator unavailability and spot-market purchases. This model does not take account of technological limitations of start-up and ramping at individual power plants. In that sense it is likely to somewhat underestimate power purchase costs.

The model is constructed using the following data sources:

1. **Power purchase contracts.** I construct a time series of MSEDCL's applicable power purchase contracts from a variety of regulatory filings with the Maharashtra Electricity Regulatory Commission (MERC), MSEDCL documents, and SLDC. Each contract is described by a variable cost in INR per kWh and a quantity in MW.

2. **Unit-level generator downtime.** In order to identify periods during which a generator is unable to deliver its contracted energy obligation to MSEDCL, I construct a panel of generator downtime at the unit level for all contracted generators from the Daily System Report of the Maharashtra State Load Dispatch Centre (SLDC).

3. **Daily unit-level generation.** I construct a time series of daily generation at the unit-level for all contracted generators from the Daily System Report of the Maharashtra SLDC.

4. **Hourly generation of must-run generation.** I construct an hourly time series of must-run generation from the Daily System Report of the Maharashtra SLDC.

5. **Hourly spot-market prices.** I use hourly market clearing prices in the day-ahead market from the India Energy Exchange for the West 2 region, which covers Maharashtra.

The basic logic of the model comes from the regulatory principle of merit order dispatch, which is required by MERC and enforced by the SLDC. This principle requires that contracted dispatchable power plants are dispatched in order of increasing variable cost, subject to limits of plant technology and grid constraints. Under this principle, MSEDCL does not choose to schedule individual power plants in each hour, but rather only a total load to serve. Plants are then dispatched according to their merit order by the SLDC, taking account of constraints from ramping, start-up, maintenance and so on. In practice, MSEDCL is required to submit 15-minute load forecasts each day for the following day to the SLDC, and then to update the forecasts throughout the day.

Critically for the instrumental variables strategy employed in the paper, MSEDCL also receives energy through must-run contracts. These contract, which it holds with hydroelectric, nuclear, wind, and solar power plants, requires MSEDCL to take all the electricity generated by the contract capacity in each hour. In effect, this inframarginal generation shifts the merit order dispatch curve as described in Figure 1.4. Or, put differently, the marginal cost of wholesale electricity is determined not by the intersection of MSEDCL's total load served and the merit order dispatch curve, but rather the intersection of its residual load after subtracting its must-run generation receipt and the merit order dispatch curve.

The steps of estimating the model are:

1. **Construct merit order dispatch curve for each hour.** While dispatchable contracts

are often for 20 years, the price and quantity is often revised. Prices generally change monthly because many contracts are indexed to coal prices on a monthly basis. Contracted quantities change less frequently, as they often require a renegotiation. Using the generator downtime data, I then remove units from the merit order for the hours during which they are unavailable. Finally, I also add realized wholesale spot market prices to the merit order, although these prices are rarely at the margin.[1]

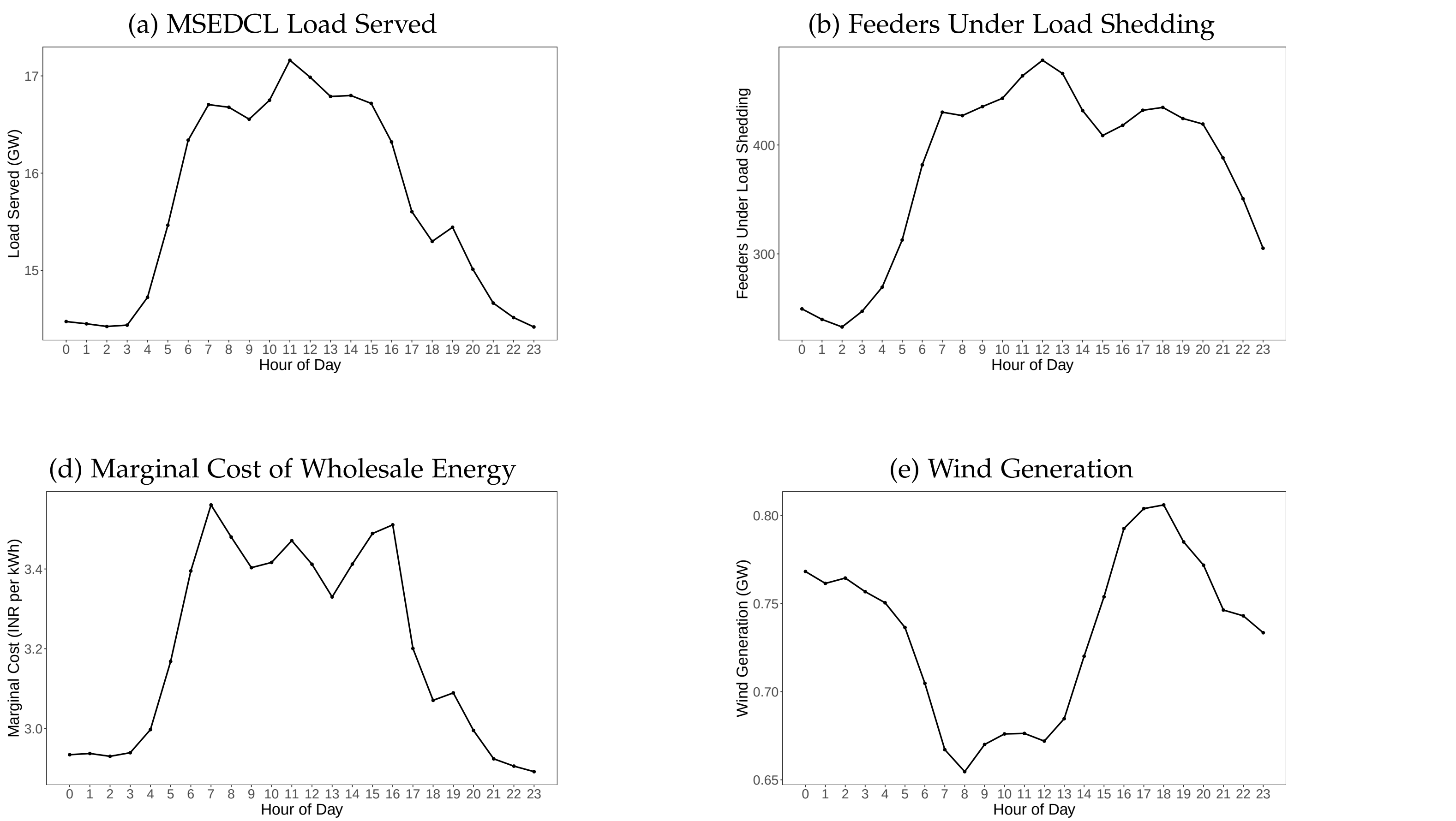
2. **Construct the residual load served by MSEDCL.** I call the difference between MSEDCL's total load served and its receipt of non-dispatchable generation "residual load."

3. **Calculate marginal cost.** The marginal cost is then calculated as the variable cost of the generator at the margin when dispatchable generators are dispatched in merit order to serve the residual load.

[1]The fact that realized wholesale spot market prices are often lower than the marginal cost of MSEDCL suggests that MSEDCL could reduce its marginal cost by simply purchasing more on the spot market. Setting aside the extent to which it may bid up the wholesale price by doing so, in practice MSEDCL is generally constrained by regulation from purchasing more than a small amount of spot market electricity during times when it is available through long term contracts.

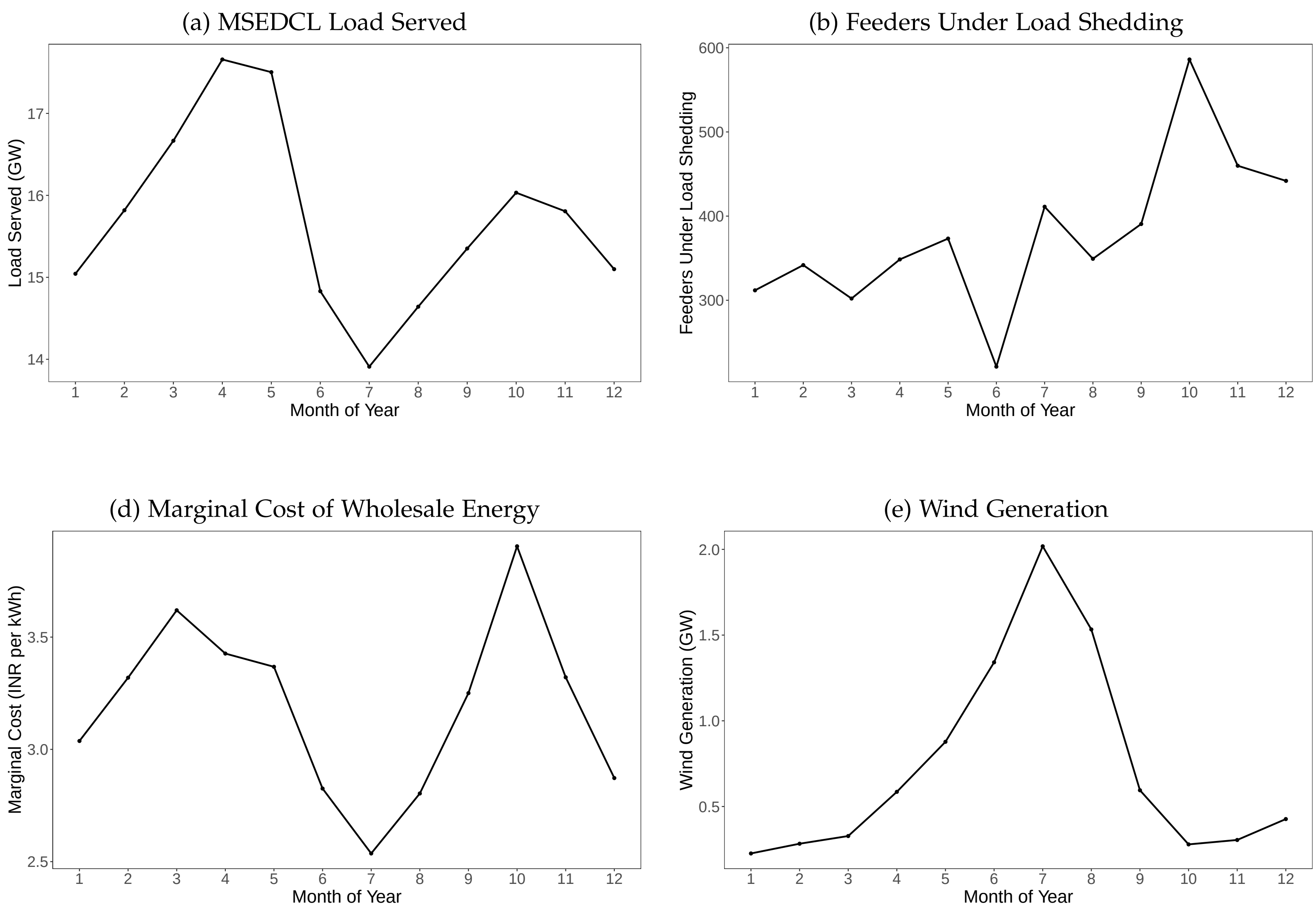
A.2 Figures

Figure A.1: *Hourly Pattern of Key Variables*



The figures plot the hourly average value of key variables used in the analysis of load shedding. Load served is the total consumption of MSEDCL customers in gigawatts (GW). The marginal cost of wholesale energy is estimated from the dispatch model described in Appendix A.1.

Figure A.2: *Monthly Pattern of Key Variables*



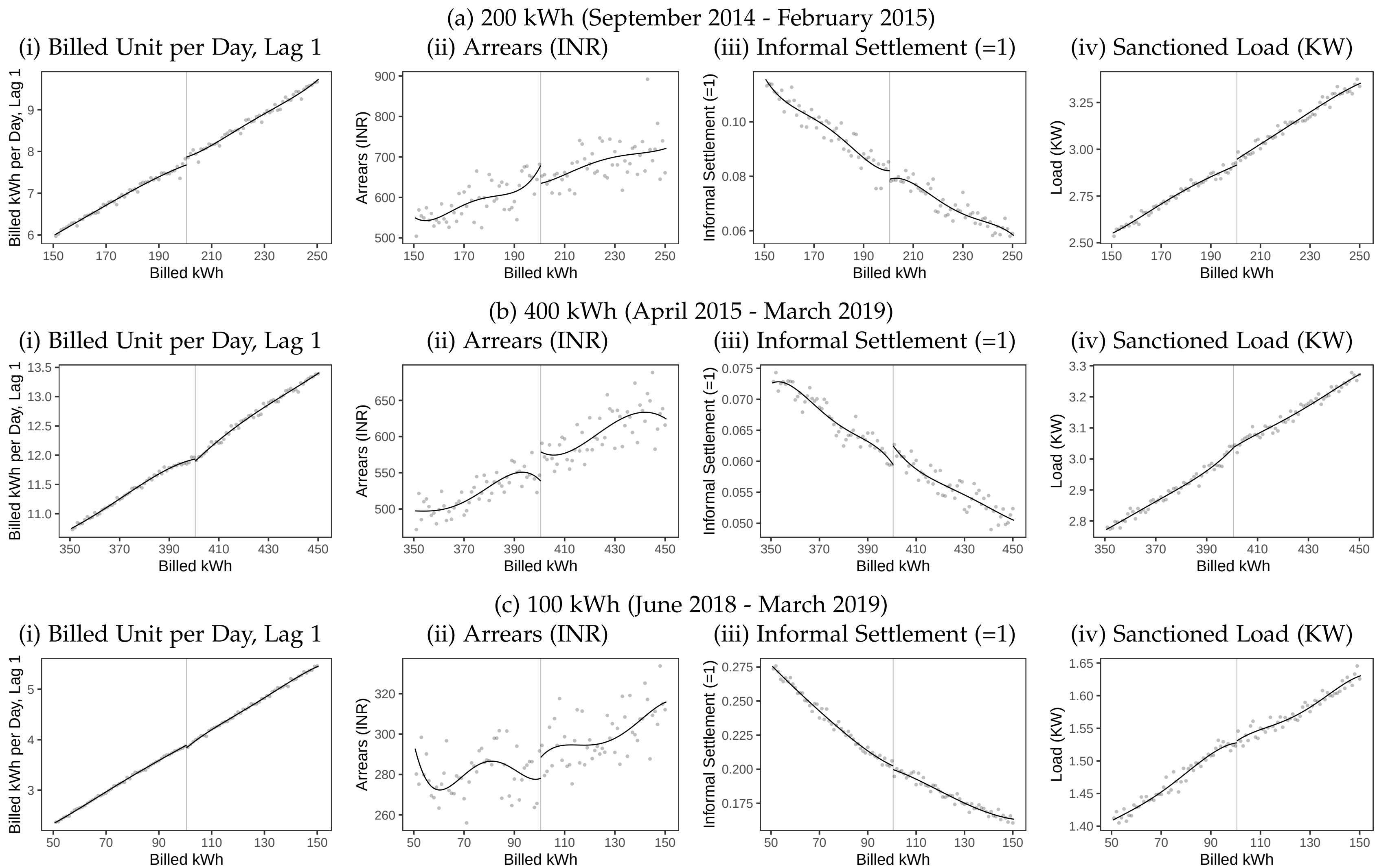
The figures plot the monthly average value of key variables used in the analysis of load shedding. Load served is the total consumption of MSEDCL customers in gigawatts (GW). The marginal cost of wholesale energy is estimated from the dispatch model described in Appendix A.1.

Appendix B

Appendix to Chapter 2

B.1 Figures

Figure B.1: *Regression Discontinuity Plots by Subsidy Notch Threshold for Covariates and Other Billing Characteristics*



The figure shows regression discontinuity (RD) plots for key billing characteristics and covariates used in the reported RD estimates of billing and payment outcomes in Table 2.3. The points represent the mean outcome in disjoint 1 kWh bins. The curves are fourth-order polynomials fit separately on each side of the threshold. The horizontal axis is billed kWh adjusted by the slab. The thresholds are located at 200.5, 400.5, and 100.5 kWh, respectively.

B.2 Estimation of Payment Rates and Arrears from Billing Records

This section describes the methodology used to infer arrears and payment rates from the billing records. The billing records include the posting date of the bill, the due date of the bill, the total charges incurred during the billing cycle, and the total amount payable on the account as of the date of posting. The difference between the total amount payable and the total charges reflects unpaid charges from prior bills. Some of these unpaid past charges may not have come due by the date that the bill posts. Therefore, we distinguish further between pending balance – unpaid charges that have not yet come due – and arrears – unpaid charges that are past due. For the purposes of illustration, the table below provides an example of a sequence of billing records. The columns in black are observed in the billing data, and the columns in red are inferred.

Posted Date	Due Date	Total Charges	Amount Payable	Paid Since Last Bill	Pending Balance	Arrears	Payment Rate
2014-09-24	2014-10-13	1887.28	1890	NA	2.72	0	NA
2014-10-28	2014-11-15	1591.35	3490	-8.65	0	1898.65	-.00457
2014-12-02	2014-12-20	855.74	870	3475.74	0	14.26	0.9959
2015-01-08	2015-01-27	552.54	1430	-7.46	0	877.46	-0.0086
2015-02-10	2015-02-28	755.95	770	1415.95	0	14.05	0.9902
2015-03-13	2015-03-31	608.75	1380	-1.25	0	771.25	-0.0016

Arrears. To calculate arrears, we subtract charges that have not yet come due, referred to as Pending Balance, from the balance on the bill:

$$\text{Arrears}_t = \underbrace{(\text{Amount Payable}_t - \text{Total Charges}_t)}_{\text{Balance}_t} - \text{Pending Balance}_t.$$

The pending balance is inferred based on the due dates of the trailing five bills. Any charges on bills not yet paid are applied to the pending balance:

$$\text{Pending Balance}_t = \max\left\{\sum_{k=t-5}^{t-1}(\text{Total Charges}_k \times \mathbf{1}\{\text{Post Date}_t \leq \text{Due Date}_k\}),\ \text{Balance}_t\right\}.$$

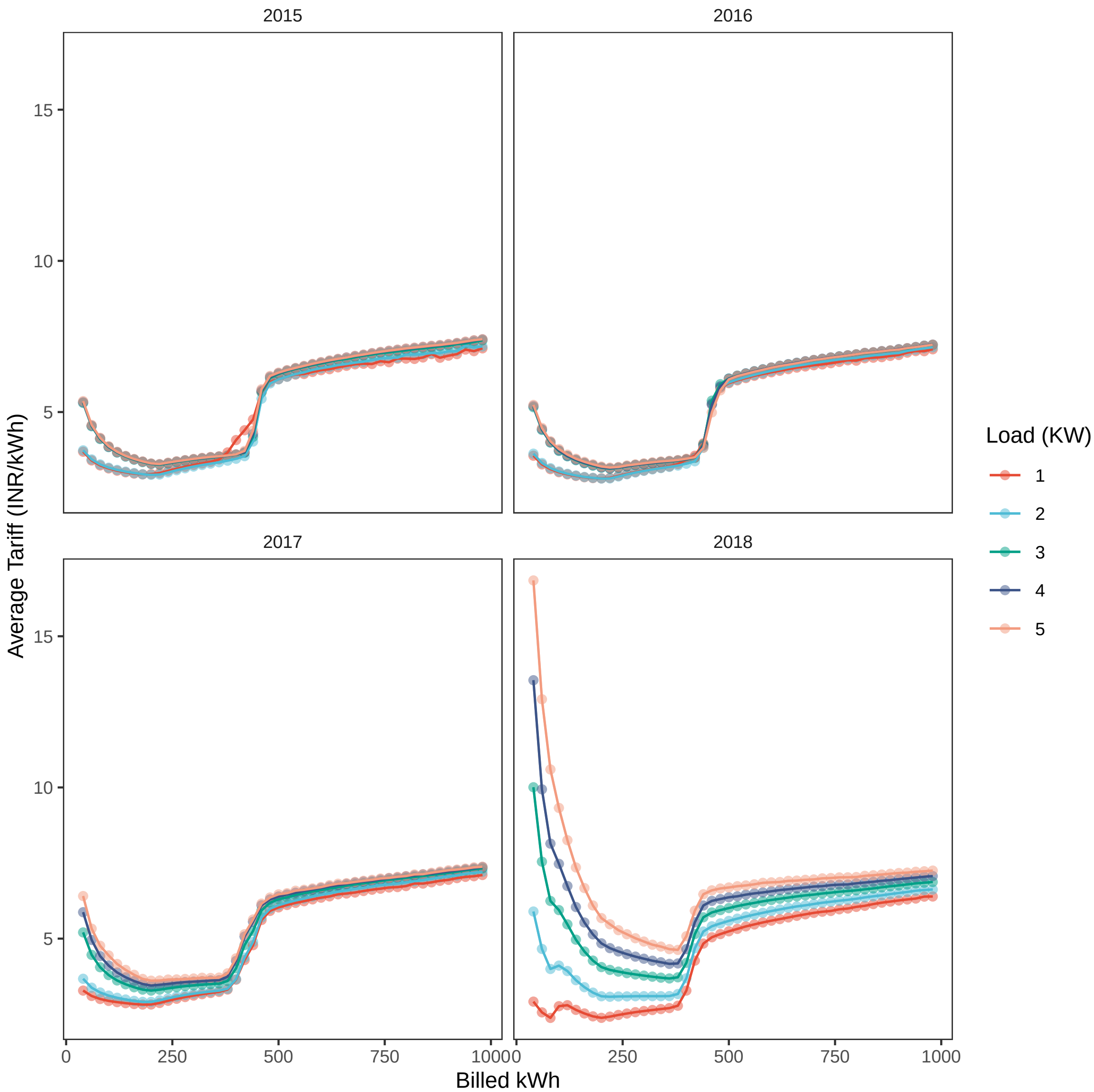
Payment Rate. The payment rate is defined as:

$$\frac{\text{Amount Paid Since Last Bill Posted}_t}{\text{Amount Payable}_{t-1} - \text{Pending Balance}_t},$$

or in other words, the proportion all charges due before the posting date of the bill that have been paid by the posting date.

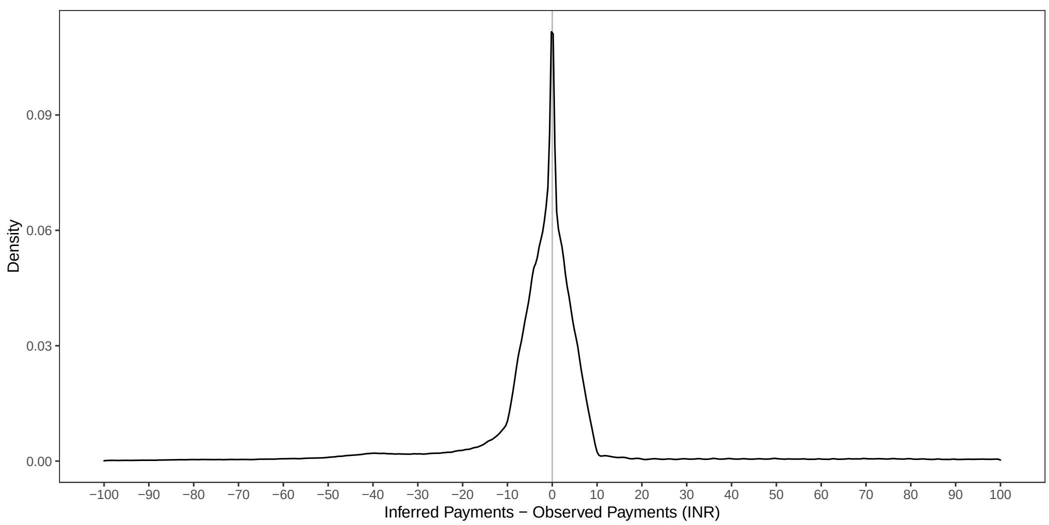
Validation. We obtained payment records for 51,005 residential customers from mid 2014 to early 2017, enabling us to validate the payment estimation for a subset of bills. When we remove negative inferred payment values, the R^2 of .83.

Figure B.2: *Average Tariff (INR/kWh) Billed to Domestic Customers, By Sanctioned Load (KW) and Fiscal Year, Mean in 20 kWh Bin*



Note.

Figure B.3: *Validation: Difference Between Inferred and Observed Payments (INR)*

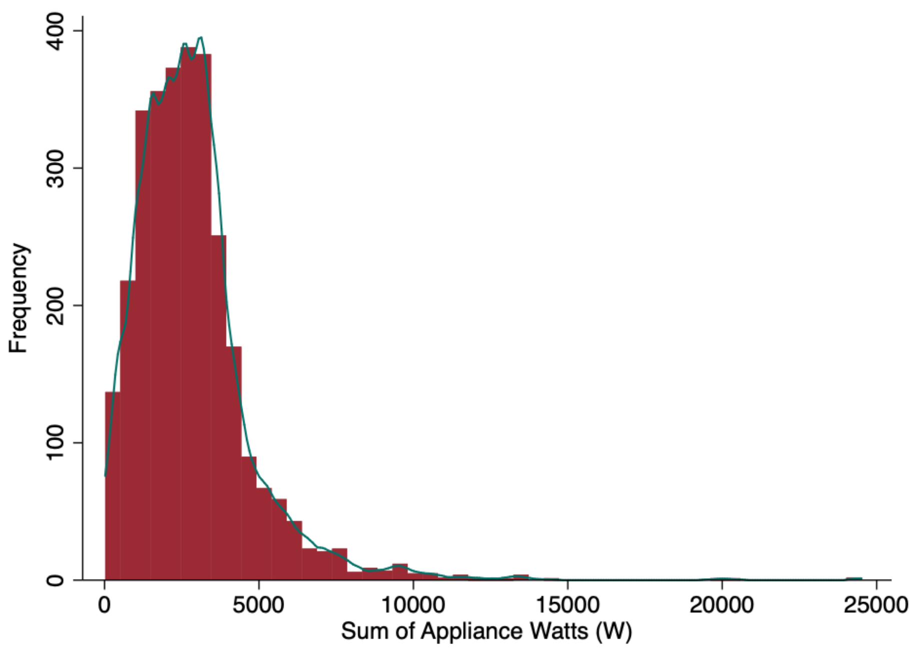


Appendix C

Appendix to Chapter 3

C.1 Figures

Figure C.1: *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.

C.2 Tables

Table C.1: *Summary Statistics of Household Survey: 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	494	339682.1	65000	0	10000000	784872.9
Rent amount	329	4216.64	3500	0	75000	4599.07
Electricity bill	3217	810.27	500	1	12000	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

Table C.2: *Summary Statistics of Household Survey: 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

Table C.3: *Summary Statistics of Household Survey: 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

Table C.4: *Summary Statistics of Household Survey: 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	20338.0	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	10320.0	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	13413.0	1	0.7	1.8
Standard X	343	3221.0	1816.1	90.0	10555.0	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	19896.0	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	13020.0	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	12474.0	8	5.6	34.8
Total	1,719	2970.5	1938.3	20.0	20338.0	142	100.0	7.7
Primary occupation of household head								
Housewife	140	3053.3	1889.7	140.0	11820.0	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	19896.0	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	12474.0	49	34.0	7.2
Retired (without pension)	36	4835.8	2844.2	600.0	13315.0	9	6.2	24.3
Pensioner	91	3554.9	1748.0	600.0	11430.0	11	7.6	10.9
Can't work due to old age or disability	155	3058.6	2147.2	110.0	20338.0	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	1,748	2983.9	1957.8	20.0	20338.0	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	10852.0	21	10.0	4.0
75,000 to 150,000 INR	1,156	2559.5	1684.4	20.0	24510.0	54	25.7	4.3
150,000 to 300,000 INR	634	3368.7	2153.4	90.0	20338.0	75	35.7	11.0
300,000 to 500,000 INR	152	4188.5	2491.4	110.0	14315.0	43	20.5	24.6
500,000 to 1,000,000 INR	37	4600.7	2762.0	380.0	11820.0	5	2.4	12.8
More than 1,000,000 INR	1	6334.0		6334.0	6334.0	3	1.4	100.0
Total	2,655	2771.0	1908.1	20.0	24510.0	210	100.0	7.3

Table C.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
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

Table C.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	3350052	3350052	3297546	3070170	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.