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Electricity Supply and Economic Growth: Evidence from a Large Experiment in Bihar*

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1 Introduction

Modern rates of economic growth depend on the use of modern sources of energy. No country has ever grown rich without vastly increasing its energy use and also moving from simple, traditional forms of energy, like human and animal power, to fossil fuels and electricity.

In search of growth, countries in Asia and sub-Saharan Africa have undertaken universal electrification campaigns to bring modern energy supply even to poor and rural areas. An estimated 1.2 billion people gained access to electricity in developing Asia from 2000 to 2019 (IEA, 2020). A striking feature of this wave of electrification is that it is happening at much lower levels of per capita income than has been common for electrification campaigns historically (Lee, Miguel and Wolfram, 2020*a*). Likely for this reason, household demand for electricity in many areas the grid has newly reached its low (Burgess et al., 2020*b*; Lee, Miguel and Wolfram, 2020*b*). The electricity grid achieves high levels of adoption and use only with heavy subsidies; otherwise, poor households may choose off-grid alternatives like solar power instead.

Are massive subsidies for grid electricity worth it? Or should countries scale back their ambitions for electricity supply in the face of low demand? Subsidizing power for the poor has a direct fiscal cost. It may also, ironically, undercut power supply to the highest-value customers, by incentivizing public utilities to ration power to limit their own losses (Burgess et al., 2020*a*). Poor power supply is one of the main complaints firms have about doing business in developing countries, according to the 2018 World Bank Enterprise Survey. The returns to a *mass* electrification strategy, as opposed to a more selective approach, depend on both household demand for power and the return to power for business firms that suffer from power rationing.

This paper describes a novel, large-scale randomized experiment in the state of Bihar in India. The experiment sought to investigate a new approach to increasing consumer payment rates as well as the relationship between electricity supply and firm outcomes. Bihar undertook in 2013 a massive electrification campaign and steadily increased both grid connections and power supply on the grid. This campaign had a high cost because of explicit tariff subsidies as well as remarkably high levels of theft and non-payment of bills (Burgess et al., 2020*a*). The state therefore limited electricity supply, circa 2014, to an average of 15 hours per day, in order to provide an adequate supply of electricity without exhausting its budget. Such power rationing is the norm in large parts of India.

We worked with the two electricity distribution companies in Bihar to test a new allocation rule for power supply in a large randomized experiment. The experiment covered the electricity supply for 1.1 million people over a period of roughly 3 years, from late 2014 to early 2018. In the experiment, a set of feeders—the lowest level of the electricity distribution network, usually serving about 2,500 customers—were randomly assigned to follow the new allocation rule. The allocation rule gave more hours of power supply to areas where losses were lower, that is to say, where consumers paid a greater fraction of their electricity bills. The experiment as a whole was introduced as 'official policy', backed by formal orders and management from the heads of the two state electricity utilities and the senior-most bureaucrat in the energy department.

Under the specified regime, the best-paying areas could earn as many as 12 hours more power per day than the worst. Because these rules connected power supply to local payments, the utility called it the Revenue-Linked Supply Scheme (RLSS). A control set of feeders were assigned to receive the average level of power supply, regardless of how much they paid for the electricity they received. The intention of this regime was to increase power supply as much as possible given a limited state budget and to incentivize increased payment for power supply.[1] The allocation rule was widely publicized through a range of methods from posters to street plays to public announcements and meetings.

We designed the experiment to study the trade-offs in electricity supply from the perspective of both the utility and its customers. On the side of the utility, we ask: did the new allocation rule incentivize greater payment and increase revenue and cost recovery? On the side of the customers, we investigate the benefits of increased power supply for those firms that received it.

We collected data from two main sources to observe both sides of this trade-off. First, administrative data, including supply log books and the utility's billing database, gives us a complete picture of the implementation of the power allocation rule and its consequences for energy supply, revenue and costs. Second, a large, representative two-wave survey of firms measures profits, revenue, inputs and technology adoption. The survey uses as a sampling frame a census of 146,497 business firms we enumerated in 8 districts under the experiment.

Measuring the returns to electricity supply from both sides of the market is critical, in our

[1] Similar rules have been adopted in, for example, the city of Karachi, Pakistan. [CITE case study on Karachi Electric by Asim Khwaja]

setting, because many grid customers do not pay for the power they receive. We will use the term "utility" to refer to the electricity distribution companies that supply power in Bihar, and "firm" to refer to a business in our sample, typically small, that may or may not use power in its operations. We calculate that the utility circa 2014 [baseline] recovers on average 52.7% of the variable cost of supply. Because many firms receive power, but do not pay for it, the demand for electricity *as estimated from payments to the utility* may be much lower than firms' actual value of electricity supply. With our survey data, we sought to circumvent this problem by directly estimating the return to electricity supply for firms, using the variation in supply induced by our experiment.

The empirical strategy built on the experiment is as follows. The treatment allocation rule links power supply to revenue from a given feeder.[2] On the side of the utility, the intention-to-treat effect of assignment to the revenue-linked supply treatment therefore measures the average effect of this linkage across feeders with different rates of payment.

On the side of customers, observe that this assignment rule, by construction, creates heterogeneity in power supply within those feeders assigned to treatment. A relatively high-paying feeder, at baseline, would be assigned a longer duration of power supply if placed in the treatment rather than the control group, wherein all feeders are assigned the average supply. Conversely, a low-paying feeder would be assigned less power supply if assigned to the treatment than to the control. Given enough variation in supply from the new allocation regime, the power supply assignment rule interacted with treatment status provides an instrumental variable that shifts the hours of power supplied to feeders, but is, by construction, uncorrelated with any other factors influencing electricity supply or economic outcomes. We investigate whether this instrument can be used to estimate the causal effect of changes in hours of supply on utility revenue and costs.

Our main results correspond to the treatment effect of the utility intervention on payments and our evidence on the effect of electricity on firm outcomes.

Treatment Effects on Payment Rates First, the treatment overall–the assignment of feeders to a revenue-linked supply schedule–did not increase utility revenue or cost recovery. We estimate small, positive effects of the assignment to treatment on revenue and revenue per unit cost, but these

[2] A feeder is the lowest metered rung of the distribution network in Bihar, with each feeder serving between 500 to 2500 consumers located in a geographically contiguous region. We will sometimes refer to this catchment area of a feeder as a neighbourhood.

effects are not statistically different from zero in our preferred specifications (see Table 4).

There are several explanations for a null effect. It is possible that the incentive was too weak, and that consumers were unwilling or unable to pay more even though they might receive better power in return. Weak incentives may also follow from the collective action nature of the new regime where an individual consumers actions may have only a small effect on payment rates in their feeder (neighbourhood) as a whole. Alternatively it might be the case that power supply does effect revenue, but that this effect is roughly linear and so the deliberately heterogeneous treatment does not change utility revenue *on average*. Finally, it is possible that the utility implemented the new regime poorly so that there was little incentive to change payment behavior *in practice* even for consumers who valued better supply greatly. The degree to which the quality of implementation matters depends on whether consumers trust stated policy initially, and whether they are able to update their beliefs about the credibility of this policy.

In our setting we find that the revenue-linked supply rule was implemented poorly. Although there was a statistically significant relationship between assigned hours of supply under the allocation regime and the actual hours delivered, the feeder level changes required by the rule are attenuated and quite noisy. A one hour change in supply as required under the allocation regime resulted in practice in a change of approximately 0.2 hours on average. Since consumers can observe the hours they actually receive, they would be able to judge whether the utility was fulfilling its promises and weak implementation may limit their response to the collective incentive. We discuss compliance and implementation issues further in Section 4.4.

Electricity Supply and Firm Outcomes To estimate the social return on power supply, we turn to our survey data, in which we can estimate the effect of power supply on firms. These impacts should be distinguished from the firms' willingness-to-pay for additional electricity — under a regime with widespread partial payment of bills, it is possible that firms benefit from electricity but are able to get away with not paying very much for it.

We begin with correlational evidence. We find that power supply is strongly associated with increases in the revenue and profits of small firms. OLS regressions of firm profits from our survey on feeder-level hours of electricity supply indicate that a one hour increase in supply corresponds to an increase by about INR 80 in profits (Table 6, Col 5). These increases are greatest for service sector firms. The difficulty in interpreting these numbers as representing a causal relationship between electricity and enterprise outcomes is that it is possible that unmeasured omitted variables in these regressions may influence both the hours of electricity supply provided to feeders, as well as firm outcomes within those feeders. For instance it is possible that political priorities may direct more public infrastructure of all types to specific feeders, so that firms getting more power also have better roads and thus better access to markets. In such a case the correlation between power supply and profits would conflate the benefits of power with those of better roads.

The experiment we conduct should in theory provide a solution to this problem by allowing us to use the treatment assignment from the experiment, interacted with baseline revenue rates, as an instrumental variable for supply. This variable shifts power supply hours for specific feeders but is by construction uncorrelated with any other factors.

Two-stage least squares regressions using only the variation induced by our experiment suggest larger impacts, with an average increase in profits from an additional hour of electricity supply of about INR 300 (Table 6, Col 1). This is about 7 percent of baseline average profits (INR 4138), suggesting a very large increase in profits from a shift from the baseline level of 15 hours of supply to 24 hours of supply. We measured firm capital using a detailed inventory of assets and their costs and paid particular care to differentiating assets that used electricity (e.g., a light bulb or a power saw) from those that do not (e.g. a table). Two-stage least squares estimates suggest that one hour of additional power supply increases electricity-using capital by INR 531 (standard error INR 157) on a base of INR 1690 but does not affect non-electricity using capital (see Table 7). There is a rich pattern of cross-sectional heterogeneity. Many manufacturing firms make up for poor power supply by generating electricity themselves, which allows them to use electricity using assets, even in the status quo. We find that the largest effects on electricity-using assets are for service and retail firms, for whom it would not otherwise be worth it to invest in the fixed cost of a generator. We also estimate that one hour of power supply increases labor demand by 1.66 person-days per month and the total wage bill by INR 5.15 on a base of INR 152.

Unfortunately these estimates are not definitive evidence of a causal link between supply and profits. Imperfect compliance with the experiment's allocation rule means that our instrument is weak. Across our results in Tables 6 and 7 we report f-statistics to show that our instrument does not pass weak-instrument tests after adjustments recommended in the modern econometrics literature.

We therefore regard these patterns as suggestive of large social returns to subsidized investment in power supply.

These results also underscore why further experimental work studying changes in firm profits and input use from better electricity in developing countries may be very informative, especially in the context of a literature that has largely focused on households.[3]

Stronger evidence on benefits to small and informal enterprises especially in rural areas may also provide a potential reconciliation within the broader literature on electrification and development. There is a tension, in this literature, between large macro estimates and small micro estimates of the returns to investment in electricity. The best estimates of the aggregate impacts of electrification, from Brazil, imply very large productivity and development gains from electricity supply (Lipscomb, Mobarak and Barham, 2013). At the micro-economic scale, though, recent experimental work finds weak household demand for electricity in rural areas of Africa and India (Lee, Miguel and Wolfram, 2020*b*; Burgess et al., 2020*b*). The value of electricity to households is below the cost of grid supply and only with subsidies can the grid compete with off-grid sources of power. These macro and micro estimates may be consistent if grid power supply has larger returns for firms than for poor households.

The remainder of this paper proceeds as follows. Section 3 describes the context of the study. Section 4 introduces the experimental design and estimates the first stage. Section 5 uses administrative data to estimate the returns to electricity supply from the utility own point of view. Section 6 uses survey data on business firms to study the returns to power supply from the firms' point of view. Section 7 concludes.

[3] A small number papers evaluate firm outcomes using quasi-experimental methods, but largely in the formal sector. Allcott, Collard-Wexler and O'Connell (2016) use variation in hydroelectric generation at the state-year level in India to estimate that shortages of power supply reduce output, but not productivity, for large, formal manufacturing plants. Hardy and McCasland (2019) find that frequent blackouts in Ghana reduce weekly revenues and profits for garment-making firms. Fisher-Vanden, Mansur and Wang (2015) use region-year level variation in potential electricity supply to estimate that firms under the threat of power shortages buy more energy-intensive inputs.

2 Context and data

This section describes the big push for rural electricity supply in India in which our experiment took place.

2.1 Electricity supply in India

From 2000 to 2020, India accounted for two-third (IEA, 2020) of the new electricity connections for households n developing Asia. This large electrification push is due to large wave of investments by the Government of India, the central government. The Rajiv Gandhi Grameen Vidyutikaran Yogana (RGGVY, Rajiv Gandhi Village Electrification Program) lasted from 2005 to 2015 and spent US$ 7.2 billion[4] during the 10th and 11th plan on distribution infrastructure and subsidies for household connections (Ministry of Power, 2013). In 2015 a new government relabeled this program as the Deen Dayal Upadhyaya Gram Jyoti Yojana (Deendayal Upadhyaya Village Lighting Program) and invested a further US$ 12.7 billion to complete the extension of the distribution grid to all rural villages (Ministry of Power, 2015). Finally, in 2017, the government launched the Saubhagya program to give free electricity connections to every last rural household (Pradhan Mantri Sahaj Bijli Har Ghar Yojana, or Pradhan Mantry Sahaj Power for Every House Program). The government invested a further US$ 2.7 billion in Saubhagya (Ministry of Power, 2021).

While these programs moved in fits and starts, collectively they have transformed energy supply in rural India. In the 2000 (KW: should be 2001 census) census, the electrification rate in rural India was 44% nationally and only 22% in a set of lagging northern states, that later would be covered by the ACCESS survey.[5] By 2018, the rural electrification rates in the lagging states had risen to 85%, according to the ACCESS survey of rural energy sources. A reasonable estimate is that the electrification rate rose by 41 pp from 2000 to 2020 [6].

This massive expansion of access creates pressure on the quality of power supply. The central government subsidized investment in infrastructure and new grid connections. Power is actually

[4]We use the exchange rate of 1 USD = 60 INR in 2018 here and hereafter.

[5]The Access to Clean Cooking Energy and Electricity – Survey of States (ACCESS) survey was conducted by the Council on Energy, Water, and Water (CEEW), an Indian think tank, to study energy poverty in six states: Bihar, Jharkhand, Madhya Pradesh, Odisha, Uttar Pradesh and West Bengal. The survey sampling design was designed to be representative of the rural population in these states.

[6]The 2000 eletrification rate was 56% according to the Census 2001, and the 2020 electrification rate was 97% according to IRES 2020.

supplied by state-owned electricity distribution companies, which have to collect from their new customers. Most rural customers pay heavily subsidized prices, below the cost of supply. Moreover, rates of collection are often low. The supply of power to rural areas is therefore rationed in order to limit utility losses (Burgess et al., 2020*a*). Despite the massive increase in electricity *connections*, the duration and quality of electricity supply in many areas remains poor. In the ACCESS survey data, circa 2018, the average rural household in a group of large northern states received 15 hours of power supply a day.

2.2 Electrification in Bihar

The state of Bihar, in this context, made its own large push to catch up on rural electrification. Bihar's rural electrification rate in the 2001 census was 44% and power supply was unreliable. In 2012, Chief Minister Nitish Kumar declared that he would not seek reelection if the power situation had not improved and began a large campaign of investment in grid infrastructure. By the ACCESS 2015 survey household electrification had risen to 41% and by 2018 to 88%. These data show the nearly incredible pace of electrification in Bihar during our study period, with 47% of households gaining access to the grid in a mere three years. On November 1, 2018, Kumar declared that electrification in the state had been completed for all willing households. There is not yet independent data from the 2021 census but it is likely that household electrification reached near-universal levels in late 2018 or shortly thereafter.

This project was conducted jointly with the utilities in the state of Bihar as they undertook their big push for universal electrification and improved power supply. There are two distribution companies, the North Bihar Power Distribution Company Limited (NBPDCL) and South Bihar Power Distribution Company Limited (SBPDCL), with service territories divided by the river Ganges, which bisects Bihar from west to east. Both companies are publicly owned and run by officers of the Indian Administrative Service. The extension of the electricity grid and the subsidized connections of many new households to the grid strained the finances of the distribution companies (hereafter, discoms). The discoms can be thought of as having soft budget constraints. While the discoms are public companies and receive subsidies for power supply, they adhere to the price-setting and cost recovery rules of an independent regulator, the Bihar Electricity Regulatory Commission. The discoms therefore face a tension between fulfilling the electrification and power supply goals of the state and balancing their budget when cost recovery is low.

2.3 Sample selection

The experiment was conducted in 8 districts of Bihar shown in Figure 3. These districts were jointly selected with the state utilities as a convenience sample on the basis of areas where infrastructural and public pressure situation allowed for controlling of hours of electricity supply.

Our primary sampling unit within a district is a feeder. The feeder is the final, 11-kV level of the electricity distribution network, before power is stepped down at local transformers for distribution to customers over service wires. A typical feeder in our sample serves a population of 2300 thousand, and includes 1730 households and 570 businesses. As new customers connect to the grid, it is sometimes necessary to form new feeders. Most often, these feeders are split off from within an existing feeder. In those cases we assign new feeders the treatment assignment of their "parent." This process is described in Appendix A.1.

2.4 Data sources

We use data from both administrative data sources and large business surveys we conducted. We begin by describing our sources of administrative data and then turn to the survey data.

2.4.1 Administrative data sources

Working with the utilities enabled access to a large amount of administrative data on energy supply and revenue collection.

Energy supply from feeder logbooks. We collected hourly data on energy supply from the logbooks of feeder operators. Feeders receive power from substations at which power is stepped down from higher voltages (often 33 kV) to a group of 11 kV feeders for distribution to villages. Substations are staffed by an operator tasked with controlling the supply of power across the feeders connected there by monitoring energy outflows and manually switching off or on the power supply to ration supply to villages. We scanned thousand pages of logbooks covering 545 feeders from 2014 through 2018. This data includes both hours of supply and the metered, outgoing quantity of energy "injected" into each distribution feeder.

Many customers in India are informal in that they are connected to the grid but may not appear in utility records or be billed regularly, or at all. An advantage of the feeder-level data is that the energy supply measure includes *all* energy supplied into the last mile of the distribution grid, regardless of whether downstream customers are then billed or have their meters read. This feature allows us to construct an accurate measure of the variable cost of power supply to the utility.

Revenue collection from billing database. We gained data from the utility on assessed energy use, billing, and the revenue collected from energy sales at a disaggregated level. During an initial period (2014 - July 2016) this data was provided by the utility aggregated to the level of the feeder. From August 2016 on to 2018, this data was provided at the level of the individual customer. Customers have unique identifiers and are mapped to a single feeder.

2.4.2 Business survey

To understand how Bihar's electricity transformation affected businesses, we conducted a large-scale and in-depth survey of businesses with an eye to their productive use of electricity.

The business survey was sampled in two stages. Within a sampled feeder, we first conducted a census of local businesses to form a sampling frame. The census recorded the location of the business and whether it was part of the retail, service or manufacturing sectors. A retail business is defined as a business that sells goods in the same condition as they are received. Any business that makes goods or processes raw materials was defined as manufacturing. We enumerated businesses regardless of whether they were connected to the electricity grid.

The second stage of sampling drew up to 40 businesses at random within each feeder. Because manufacturing firms are less common, and we believed they would be especially likely to benefit from better electricity supply, we sampled all manufacturing businesses enumerated. With these rules, we then surveyed a total of 5,620 businesses representing an enumerated population of 146,497 businesses within our sampled feeders.

A major advantage of our firm data collection is that it is representative of the many and various types of small businesses in Bihar. Prior work on the effects of electricity supply on business has often been confined to large, formal manufacturing firms due to data constraints (Allcott, Collard-Wexler and O'Connell, 2016; Fisher-Vanden, Mansur and Wang, 2015).

The survey instrument is original and measures firm inputs, capital assets, outputs, revenue and profit. We ask businesses about whether they have electricity from the grid and from alternate sources like diesel generators as well as the duration of electricity supply in the last month. The instrument measures all inputs, including labor, capital, materials and energy. We take particular care to distinguish between different kinds of capital assets on the basis of whether they use electricity (e.g., a light bulb or an electric saw), do not use electricity (e.g., a cupboard or hand tool), or generate electricity (e.g., a diesel generator or solar panel).

3 Power supply for businesses at baseline

This section uses our administrative and survey data to present four facts that motivate our experimental design. We show that the duration of power supply each day is low; that payment rates for power are low and unrelated to the duration of supply; that businesses are only partially electrified; and that businesses invest, at substantial cost, to substitute for erratic grid power supply.

3.1 Power supply is low

Figure 1 shows the distributions of power supply at baseline (top row) and endline (bottom row). Within each row, the histogram at left shows power supply hours per day from administrative data, while the histogram at right shows power supply hours from survey data. The average daily power supply hours at baseline is 15.68 (standard deviation 3.22) hours per day in the administrative data and 11.10 (standard deviation 5.68) hours per day in the survey data.

The survey data generally reports lower hours of power supply for two reasons. One is that there may be very local outages, for example due to a blown transformer, that are not visible at the level of grid power supply in the administrative data. The second reason is that businesses may mistakenly report use of power or consider only hours when the business is operating, even though the survey asked explicitly about hours of supply over the entire day.

By either measure, businesses experience at least 8 hours without power on average. Nor do these hours come in the middle of the night. The peak time for power use is the six hours in the evening from 5 to 11 pm. During this evening peak, businesses on average receive 2.91 hours of supply (standard deviation 1.58 hours), according to the business endline survey data measure.

3.2 Payment rates for power are low

The rate of payment for electricity supply is also low as a share of the cost of supply. To describe rates of payment, let $Revenue_{it}$ be the payments for electricity supply from customers in feeder i in month t, $Energy_{it}$ be the quantity of energy supplied to that feeder in kWh, and $Price_{it}$ be the weighted-average tariff for its customers in INR per kWh. The rate of payment in feeder i is then

$$RevenueRate_{it} = \frac{Revenue_{it}}{Energy_{it} \times Price_{it}}. \tag{1}$$

Assume that tariffs are reflective of costs. This assumption is reasonably accurate, since by regulation tariffs *gross* of government subsidies must be set within 20% of cost recovery for all categories of customers. A $RevenueRate_{it}$ of zero means that none of the variable cost of energy supply is recovered by the utility from energy revenues. A $RevenueRate_{it}$ of one means that a feeder pays for all of the energy it is supplied.

The $RevenueRate_{it}$ measure is an overall measure of cost recovery at the feeder level. This measure represents the gap between revenues and costs for the utility *before* state government subsidies for energy supply. Because the state government subsidizes energy consumption, the $RevenueRate_{it}$ does *not* represent utility losses; the utility makes up part of the cost recovery gap from state government subsidies. We prefer using revenue rate as our measure of cost recovery because it reflects the cost recovery of the state and utility considered together. Forming a measure of cost recovery from the view of the utility alone would require parsing the effect of additional energy supply on state subsidies to the utility.

Figure 2, derived from Figure 2 in Burgess et al. (2020*a*), shows the distribution of payment rates across feeders on the horizontal axis and the relation of payment rates to hours of supply. There are two main points from the figure. First, the average feeder returns 31% of the variable cost of the energy it consumes. A 79% share of feeders return less than half of the cost of energy they are supplied. Second, there is no relation between local payment rates and hours of supply received. The coefficient from a linear regression of average daily supply hours on $\overline{RevenueRate_{it}}$ at the feeder level controlling for region and urban is -0.980 (standard error 0.819). Higher-paying areas therefore do not receive more hours of power supply than areas that do not pay for power.

3.3 Firm electrification is incomplete at baseline

We now turn to describe the businesses in our sample. We focus in particular on the experience of businesses with electrification and power supply. Table 2 provides summary statistics on our sample businesses. The businesses in our sample are mostly small. From Table 2, the average business has 1.61 employees and earns INR 4,539 of profit per month on revenue of INR 21381. Businesses are labor intensive. The average monthly wage bill is INR 6,454 (42 days of work at roughly INR 160 per day), while the total capital *stock* is about INR 16,000. While most businesses are small there is a right tail of larger firms. The standard deviation of profits is INR 7,627 per month and of revenue INR 69,778 per month, more than three times the mean.

At baseline in 2014, 58% of the businesses in our sample are connected to the electricity grid, and they report an average of 15 hours of electricity supply (standard deviation 5 hours). The average business owns two light bulbs but the median business owns none. Appendix Table A5 and Table A6 show appliance ownership by business at baseline and endline respectively. The five most common electrical appliances owned in baseline are: bulbs, fans, tubelights, electric weights, and refrigerators for retail firms, bulbs, fans, tubelights, printers, and desktops for service firms, and bulbs, fans, drills, electric weights, and electric saws for manufacturing firms. The applicance classification into electricity using and non-electricity using assets can be found in Appendix A.2.

3.4 Firms invest to substitute for poor grid power

While 42% of businesses are not connected to the electricity grid, this does not imply that electricity is not an important input. Appendix Table A4 breaks out business characteristics by firm type. In our sample, 44% of firms are retailers, 44% service and 12% manufacturing firms. While manufacturers are a small share of firms they pay wages about 50% higher per day than retail firms and hire 60% more labor days in a month. The greatest share of retail firms (62%) are connected to the grid while less than half of manufacturing firms are connected. The reason is that manufacturing firms appear to substitute for grid power by using off-grid sources of power.

Our survey collected detailed asset rosters to distinguish between capital assets that do not use electricity, assets that use electricity, and assets that generate electricity, including diesel generators and solar panels. Figure **??** summarizes this data at baseline and endline. Mean investment in electricity-generating capital is INR 431 among retail firms, INR 2168 among service firms, and INR 8235 among manufacturing firms. The latter number, for manufacturing firms, is greater than their investment in electricity-using capital (INR 5693) and 30% of total capital investment. That is, manufacturing firms spend more on capital to generate electricity—even before accounting for variable generating costs—then they do on capital that actually uses electricity.

The baseline power supply conditions for firms are therefore poor. About half of firms are electrified and power is available about 15 hours per day for those on the grid. Firms in the manufacturing sector cope with these shortages with significant capital expenditures in their own generation.

4 Experimental design

This section describes the design of the power supply experiment. The treatment we study is a connection between power supply and local rates of payment for electricity.

4.1 Treatment design: Revenue-linked supply

The experimental treatment is to connect the scheduled power supply for a feeder to its rate of payment for electricity. The experiment was therefore known as the "Revenue Linked Supply Scheme," or RLSS, because it assigned the hours of supply that a feeder was supposed to receive on the basis of past payments. In the control group all feeders were assigned the average level of power supply.

4.1.1 Power supply assignment rule

To describe the mechanism of the treatment precisely, it is useful to define several variables.

The power supply assignment rule is a function from revenue rate to hours of supply with two steps. First, each value of $RevenueRate_{it}$ is mapped to a power supply "bin." The *initial* bin assignment of the feeder is denoted

$$Bin_{i0}(RevenueRate_{i0}) = \begin{cases} 1, & \text{if } 0 \leq RevenueRate_{i0} < r^1 \\ 2, & \text{if } r^1 \leq RevenueRate_{i0} < r^2 \\ 3, & \text{if } r^2 \leq RevenueRate_{i0} < r^3 \\ 4, & \text{if } r^3 \leq RevenueRate_{i0} < r^4 \\ 5, & \text{if } r^4 \leq RevenueRate_{i0} \end{cases}$$

where r^b denotes the upper bound on revenue for a feeder to be assigned to bin b. The vector of revenue rate cut-offs in the experiment is $r = \{0.15, 0.3, 0.45, 0.6\}$. Second, each feeder is assigned to a number of hours of supply depending on their revenue rate, whether the feeder is urban or rural $U_i \in \{0, 1\}$ and whether the discom was North Bihar ($North_i = 1$) or South Bihar.

Table 1 gives the power supply assignment function $HoursAssigned_{it}(Bin_{i0}, U_i, N_i)$ at the start of the experiment in 2014. The power supply schedules were set by the leadership of the power distribution companies with reference to the range of existing power supply conditions and their goals for supply in different areas of their respective companies. All treatment feeders were assigned power supply on this schedule. The range of power supply between the lowest and the highest bins is between 8 and 12 hours per day. Increasing payment rates would therefore have a large effect on power supply under the treatment schedule. The average supply assigned, of 16 to 20 hours, was meant to be reflective of the actual average supply in Bihar at the time. The supply schedule was shifted upward uniformly in 2016 and again in 2017 to reflect increasing power supply throughout the state while maintaining the distinction between the lowest and highest bins. At any given time, all control feeders were assigned to the third, middle bin of the power supply schedule.

4.1.2 Discussion

The treatment was intended to have two effects. First, a reallocation effect, in which the distribution company's existing supply was shifted towards feeders that paid at a higher rate. If that higher payment rate was applied to the new energy supply to a feeder, this reallocation would be expected to increase the aggregate revenue of the company. With greater revenue, the discoms could use a looser budget constraint to allow an expansion of power supply. Second, an incentive effect, in which feeders were collectively incentivized to pay more in order to increase their power supply over time.

In order to promote an incentive effect, the program was aggressively marketed and the distribution company updated the bin assignments at intervals over the course of the experiment. Marketing campaign were conducted across four media: SMS notifications, bill inserts, announcements, and posters. Text messages informing consumers about the RLSS scheme were sent through SMS to registered mobile numbers. Pamphlets were attached to bills (bill inserts) containing feeder specific information on RLSS. Public announcements advertising the RLSS scheme was done using a moving vehicle. Posters were placed in prominent places during announcements. A summary of total distribution count, people reached, total cost, and duraction can be found in Table A1.

The prospect of power supply improvements can only incentivize higher payments if power supply schedules are updated to reflect changing payment rates. The discoms therefore updated the power supply bin assignments at intervals to reflect changes in payment rates. In North Bihar, the initial assignments were done in October, 2014. They were thereafter updated in April, 2015, January, 2016, July, 2016 and October, 2017. In South Bihar, the initial assignments were done in December, 2015. They were thereafter updated in July, 2016, April, 2017 and January, 2018. Table 1 shows the power supply schedules for each of these updates.

4.2 Treatment assignment and experimental integrity

The treatment was phased in over time beginning in 2014. The experimental sample comprised of 341 total feeders in both discoms. Within each of 6 waves of treatment assignment, half of sample feeders were assigned to treatment. The randomization was done stratified on the variables of region and division.

Table A2 and Table A3 describe the balance of the experimental treatment on characteristics measured in both the administrative and the survey data. The survey data, collected at the firm level, has been collapsed to feeder-level means. Treatment and control are well balanced.

4.3 Regression specifications

The experimental design is somewhat non-standard in that the treatment is deliberately heterogeneous: feeders with a high baseline rate of payment initially will be assigned more power supply, relative to the assignment in the control, while feeders with a low rate of payment will be assigned less power supply. We therefore create several specifications that look at the effect of assignment to treatment and, separately, that use the experiment to generate instrumental variables for power supply.

4.3.1 Intent to treat specifications

The simplest specification is a difference-in-difference specification comparing treatment feeders before and after treatment assignment. As above i denotes a feeder and t denotes a month.

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 Post_{it} + \beta_3 T_i Post_{it} + \varepsilon_{it}. \tag{2}$$

The outcome variable Y_{it} may be hours of supply, energy supply, the revenue from energy sales or the revenue rate. Standard errors are clustered at the feeder level to account for serial correlation. In many specifications, we also omit the T_i main effect in favor of feeder fixed effects. We also expand the above into an event-study specification by replacing the $\beta_3 T_i Post_{it}$ interaction term with a series of interactions $\sum_\tau \beta_\tau T_i \mathbf{1}\{t = \tau\}$ for event time τ months relative to the treatment assignment. The coefficient β_τ then gives the effect of treatment assignment on the outcome τ months after the treatment started. Because the treatment was phased in, the τ is defined relative to the time of assignment for each cohort, and event time is not perfectly collinear with calendar time.

Treatment assignment is expected to have heterogeneous effects by the nature of the treatment. To fix ideas, consider energy consumption as the outcome and suppose that compliance with assignments was perfect (we discuss actual compliance in part 4.4 below). Since the assignment schedule Table 1 is symmetric about the mean hours of supply, assignment to treatment would be expected to have no immediate effect on energy consumption if (a) energy consumption is linear in hours of supply (b) there is no anticipatory incentive effect on payment that increases supply and therefore energy consumption in the treatment group. In this case, any increase in supply and energy consumption in high-paying areas would be offset by a corresponding decrease in low-paying areas. If, however, there is an incentive effect of the treatment that increases payment rates, then the assignment to treatment itself may cause higher payments, supply and energy consumption.

4.3.2 Instrumental variables specifications

To use the heterogeneity induced by the treatment, our analysis will mainly rely on instrumental variables specifications that use the experiment to generate instruments for hours of power supply.

A main concern with the analysis of data on business profits and power supply, as introduced in Table 2 and Table A4, is that firm use of power and the supply of power are both endogenous decisions. Firms that are more productive may invest in generators to sustain output despite power shortages (Allcott, Collard-Wexler and O'Connell, 2016). The discoms may also supply more power to areas that are considered vital for economic or social reasons. Our experiment provides powerful instruments to estimate the causal effect of power supply on a range of outcomes for both the discoms and firms.

There are two main instrumental variables specifications. The first specification uses the treatment to form a variable $HoursAssigned_{i0}$ for power supply assignment and uses that variable as an instrument. Specifically, we follow Table 1 to form

$$\begin{aligned} HoursAssigned_{i0} \quad = \quad & (1-T_i)\left(\sum_{N=0}^{1}\sum_{U=0}^{1}\mathbf{1}\{North_i = N\}\cdot\mathbf{1}\{Urban_i = U\}\cdot HoursAssigned_{NU}^{b=3}\right) \\ & T_i\left(\sum_{N=0}^{1}\sum_{U=0}^{1}\sum_{b=1}^{5}\mathbf{1}\{North_i = N\}\cdot\mathbf{1}\{Urban_i = U\}\cdot Bin_{i0}^{b}\cdot HoursAssigned_{NU}^{b}\right). \end{aligned}$$

This function has indicators for each combination of the urban and North dummy variables and a feeder's payment bin Bin_{i0}^{b}. All of the possible feeder categories created by the interactions of these variables are themselves interacted with treatment assignment. At a given time, therefore, there are 4 possible assignments in the control group (Table 1, row $Bin_{i0} = 3$ and 20 possible assignments in the treatment group (Table 1, all cell entries).

A note on timing. The actual hours assigned in the experiment $HoursAssigned_{it}$ used the revenue rates as of month t to calculate a feeder's bin assignment over time. In the construction of the instrument, we use the initial hours assigned $HoursAssigned_{i0}$, based upon the feeder's initial payment rate at the start of the experiment. The reason is that the dynamic hours assignment depends on payment rates and therefore potentially on the response to the experiment. The static, initial hours assignment is preferred as an instrument because it is based only on pre-determined characteristics and their interaction with treatment assignment.

With the assigned hours so constructed, our simple instrumental variables specification is:

$$
\begin{aligned}
Y_{it} &= \beta_1 Hours_{it} + \sum_{N=0}^{1}\sum_{U=0}^{1}\sum_{b=1}^{5} \mathbf{1}\{North_i = N\} \cdot \mathbf{1}\{Urban_i = U\} \cdot Bin_{i0}^{b} \cdot \beta_{NU}^{b} + \\
&\quad \beta_2 X_{it} + \varepsilon_{it} \qquad (3) \\
Hours_{it} &= \alpha_1 HoursAssigned_{i0} + \\
&\quad \sum_{N=0}^{1}\sum_{U=0}^{1}\sum_{b=1}^{5} \mathbf{1}\{North_i = N\} \cdot \mathbf{1}\{Urban_i = U\} \cdot Bin_{i0}^{b} \cdot \delta_{NU}^{b} + \\
&\quad \alpha_2 X_{it} + \nu_{it}. \qquad (4)
\end{aligned}
$$

Equation (3) is the structural equation for how hours of supply affect feeder-level outcomes. Equation (4) is the first stage. We use assigned hours to instrument for hours. The structural equation and the first stage both include controls for the main effects of the pre-determined variables that enter the hours assignment. Within the bins determined by these controls, variation in assigned hours comes only from the treatment assignment.

Our second specification is closely related to the first but allows for more flexibility in compliance in the experiment. In essence, using (4) as the first stage assumes that assigned hours have the same coefficient α_1 in both discoms and all areas. With imperfect compliance, the effect of assigning an additional hour on hours supplied may itself be heterogeneous across feeders. We therefore use an alternate, saturated first-stage specification

$$
\begin{aligned}
Hours_{it} &= T_i \cdot Post_{it} \cdot \sum_{N=0}^{1}\sum_{U=0}^{1}\sum_{b=1}^{5} \mathbf{1}\{North_i = N\} \cdot \mathbf{1}\{Urban_i = U\} \cdot Bin_{i0}^{b} \cdot \alpha_{NU}^{b} + \\
&\quad \sum_{N=0}^{1}\sum_{U=0}^{1}\sum_{b=1}^{5} \mathbf{1}\{North_i = N\} \cdot \mathbf{1}\{Urban_i = U\} \cdot Bin_{i0}^{b} \cdot \delta_{NU}^{b} + \\
&\quad \alpha_2 X_{it} + \nu_{it}. \qquad (5)
\end{aligned}
$$

This specification does not assume that one hour of assigned supply yields the same effect on hours in all bins. Rather, the effects α_{NU}^{b} of assignment to each bin on supply hours can be heterogeneous by urban, north and payment bin.

4.4 First-stage effects of treatment on power supply

This section estimates compliance with the experiment and establishes that assignment to treatment varied power supply.

Table 3 presents estimates of the simple first-stage specification (4). The first set of columns 1 to 4 restricts the sample to feeder-month observations prior to the start of the treatment. The second set of columns 5 to 8 restricts the sample to feeder-month observations after the start of the treatment. Within each group of columns, the first pair of specifications regresses hours received on the dynamic assignment $HoursAssigned_{it}$, based upon contemporaneous payment rates. This variable is constructed using the same assignment rule prior to the treatment assignment as afterwards. The second pair of specifications regresses hours received on the static initial assignment $HoursAssigned_{i0}$.

Across specifications there is not generally a significant relationship between hypothetical assigned hours and hours received before the treatment started. The coefficient on $HoursAssigned_{it}$, in column 1, is -0.0302 hours (standard error 0.109 hours). Column 2 adds month fixed effects and again finds there is no effect of assigned hours on hours received before treatment. Columns 3 and 4 use the static assignment $HoursAssigned_{i0}$ which also suggests no relationship.

The right side of Table 3 shows statistically significant but attenuated effects of assigned hours on actual hours after the treatment starts. For example, in column 5 being assigned to one more hour of power supply is estimated to increase power supply by 0.199 hours (standard error 0.0538 hours), or 12 minutes for each hour assigned. The coefficient remains similar at 0.216 hours (standard error 0.056 hours) when including month fixed effects (column 6). This coefficient on dynamic assigned hours is our overall estimate of compliance: how well actual power supply tracked assigned hours during the experiment. However, it overstates the strength of the first stage, since the static assigned hours in the first stage are based upon only *initial* payment rates. Columns 7 and 8 show that assigned hours based only on initial payment rates have a positive but small effect on hours. As expected, since initial assigned hours are only a prediction of what hours will be assigned later, the first-stage coefficients using static or initial assigned hours are smaller than for dynamic assigned hours. In Row 4 we report f-statistics corresponding to this first-stage. These estimates make clear that the consequence of limited compliance is to weaken the instrument.

Figure 4, to investigate balance and compliance, plots the coefficient on the first stage assigned hours over time from the modified event-study version of (4). The estimated coefficient on assigned hours is close to zero and statistically insignificant during the six months for which we have pre-treatment supply data. The coefficient then rises, after the treatment starts in late 2014, but fluctuates around 0.2 hours per assigned hour for the full treatment period of over three years. It is statistically insignificant in the first year of treatment although the variance in supply improves after the assembly elections. Overall it is clear that the policy had only a weak impact on actual supply.

These results on compliance are interesting in themselves. They reflect some of the challenges high level policymakers face in implementing utility policy. The Revenue Linked Supply Scheme was implemented with orders from utility leadership, and over the three year period we study, very senior government officials including the executive heads of the distribution utilities and the Secretary of the Department of Energy presented the scheme at different fora within and outside the state. We are therefore confident in policy intent to implement.

Notwithstanding the orders of management, modifying actual electricity supply in Bihar depends on the actions of a large number of field engineers. The utility in Bihar did not possess centralized SCADA infrastructure to remotely set supply schedules for its different feeders. As a result the allocation regimes had to be implemented by sending instructions to field offices telling them when to cut power and for how long. The utility engineer in these offices would then have to physically 'flip a switch' to turn supply on or off. Field engineers do not necessarily carry out the instructions they are given and are government employees with secure jobs. Their decisions to depart from written rules may be independent or may be a response to external factors including political pressure and threats of violence from the public, occasional instructions to provide more power to everyone during festivals or hot days, as well as unexpected technical faults. In other words, there is evidently a significant amount of administrative friction that serves to weaken the link between what the government utility may state as official policy and what it can actually force its staff to implement. These issues of state capacity affected our experiment but are broadly relevant to understanding why state-run distribution utilities may find it difficult to implement reforms or innovations to usual operating practice.

5 Returns as viewed from the supply side

This section uses the experiment to investigate the returns to offering a power supply schedule from the perspective of the discoms.

5.1 Intention to treat: effects of the assignment to a supply schedule

Table 4 presents estimates of the intention to treat specification (2). The table shows regressions for the three different outcomes of feeder energy consumption, net revenue collection and the revenue rate. Each odd-numbered column shows the basic difference-in-difference specification and each even-numbered column additionally includes feeder fixed effects.

The assignment to treatment is estimated to have statistically insignificant effects on energy consumption (column 2), net revenue collection (column 4) and revenue rate (column 6). We prefer specifications with feeder fixed effects because feeder-level revenue is skewed and can be affected by the presence of a few large customers. The mean revenue rate, the dependent variable in columns 5 and 6, is only 0.37. The estimated effect of the program on revenue rates is either 0.0115 (standard error 0.0535), without feeder fixed effects, or 0.0346 (standard error 0.0346), with fixed effects.

The assignment of treatment feeders to a power supply schedule connected to supply did not increase utility revenues or cost recovery over a period of three years. These estimated null effects show that there was no large incentive effect of the power supply schedule on payments over time. Because *average* supply in the treatment was unchanged, relative to the control, by design, these estimates do not imply that power supply itself does not affect energy consumption or revenues. The next part uses the heterogeneity induced by the experiment to study the effects of power supply itself.

5.2 Instrumental variables: effects of an hour of supply

Table 5 presents instrumental variables estimates of (3). In odd-numbered columns we use (5) as the first stage. In even-numbered columns we replace bin controls with feeder fixed effects in both the structural equation and the first stage. The dependent variables are energy consumption, revenue and the revenue rate, as described for Table 4.

The instrumental variables results are highly imprecise and we cannot reject the null of no effect on energy supply cost or revenue. These estimates are consistent with the diff-in-diff results summarized in the last section.

6 Returns as viewed from the demand side

This section estimates how increases in power supply affect firm profits and input choices.

6.1 Profits and revenues

Table 6 presents instrumental variables estimates of (3). Here and for the specifications below, the first stage is a version of (5) with the variable $Post_{it}$ removed (to account for the fact that the regression is run in the endline survey data, rather than in a monthly panel, as was the case with the administrative data). In the survey data each observation is a firm. We include controls for the baseline value of the dependent variable and cluster standard errors at the feeder level, at which the treatment was assigned.

The main result in Table 6 is that one additional hour of electricity supply is estimated to increase business profits by INR 297.4 per month (standard error 145.8) per month (column 1). Relative to the mean baseline level of profit of INR 4138 per month, this estimate represents a 7% increase in profits *per hour* of power supply.

The effect of power supply on profits is estimated to be largest for manufacturing firms (column 4). The point estimate for manufacturing firms is that one hour of power supply increases profits by INR 675.5 (standard error 261.1), or 15% of the baseline mean. This estimate is more than twice as large as in the overall sample of all firm types. The estimate for the effect of hours of supply on profits for retail firms is INR 152.8 (standard error 189.9) (column 2) and for service firms INR 286.9 (standard error 145.2) (column 3). Table 6, columns 5 through 8 show OLS estimates when regressing profits on hours of supply. As we might expect these are attenuated relative to IV estimates. Panel B scales up the Panel A coefficients by the number of firms per feeder in the baseline census, to provide an estimate of the treatment effect at the feeder level.

These results suggest heterogeneity of the effects of electricity supply by firm type. Manufacturing firms, which are more energy dependent, see profits rise without a notable increase in revenues. This result suggests that increases in power supply must have reduced costs or otherwise increased productivity. Service firms, which have a large wage bill as a share of revenues, have increases in profits driven by large increases in revenues. For retail firms, which sell goods in the condition received, power supply has a small estimated effect on profits.

Unfortunately, as Table 6 reports, the adjusted f-statistics for these IV regressions is well below critical thresholds suggested in the modern econometrics literature. As a result these results are best interpreted with significant caution - suggestive of an important link between electricity supply and business outcomes, but not definitive evidence.

6.2 Input choices

Table 7 uses the same instrumental variables specification to provide a summary view of how power supply changes firm input choices. The sample includes firms of all types. The four main headers cover labor, capital, materials and land inputs. Within each main header the table has a column or several columns with alternate measures of that input. We find that an hour of power supply causes economically significant increases in labor, capital and land inputs but has no effect on materials inventory.

For labor, an hour of supply increases total labor earnings at a firm by INR 486.6 (standard error INR 174.6), or 8% of the baseline wage bill. This effect is a composite of a 1.7 (standard error 1.0) increase in days worked and a INR 5.1 (standard error INR 1.4) increase in the wage (3% of the baseline wage). The sample size is smaller for labor specifications than in our overall sample because many firms have only a proprietor, and we define labor input to exclude the proprietor.

For capital, an hour of supply increases the value of the capital stock at a firm by INR 1738.2 (standard error 725.1), or 16% of the baseline value (column 4). Our survey contained detailed asset rosters to distinguish types of capital that use electricity, that do not use electricity, and that generate electricity. We find a large effect of hours of supply on electricity-using capital with a coefficient INR 530.9 (standard error 157.4). This estimate makes economic sense: power supply ought to be complementary to electricity-using assets. There is also a positive and large estimated effect of power supply on non-electricity using capital, but this estimates is less precise. There is a null effect of power supply on electricity generating capital such as diesel generators and solar panels.

For materials, we estimate a null effect of power supply on inventory. Firms do not keep more goods in stock when supply improves.[7] Finally, power supply increases building rents (column 9). The sample in this column is restricted to firms that pay rent rather than own their own premises. Therefore an increase in rent can be interpreted as reflecting an increase in electricity bills rather than an increase in the value of the premises.

As with our evidence on profits however, these estimates also suffer from a weak-instruments problem, and therefore should be treated with some caution.

7 Conclusion

The experiment we conducted was designed to create a collective incentive rewarding feeders where population payment rates rose. This incentive in practice was weak because the utility was unable to enforce compliance with the stated schedule, notwithstanding high-level support, official policy notifications, and multiple organizational efforts to increase adherence to the schedule. This low compliance underscores the difficult utilities in developing countries might face in implementing policy interventions that require the coordinated action of hundreds of ground staff, especially in settings where external pressures also act on employees. In developed countries, and even some of the richer states in India, utilities are typically able to cut and restore power in real time and in a centralized manner. These supply instructions can be executed at different levels of the grid, from the feeder down to even individual consumers. None of these advantages were available to the utility in Bihar at the time of this experiment, and therefore whether power flowed in a feeder at any given time required a human being to flip a switch.

Our data collects outcomes on small and mostly informal-sector firms, that are not represented in national surveys such as India's Annual Survey of Industry. As a result very little prior evidence, causal or otherwise, exists on the relationship between firm outcomes at this scale and power supply. Nevertheless, these firms are at the frontier of enterprise activity and consequent income generation in rural India. The low compliance that we observe with the schedule set out in the Revenue Linked Supply Scheme creates difficulties in using the design of the experiment - which theoretically creates exogenous variation in electricity supply - as a means of cleanly identifying the effects of electricity

[7] The sign of any inventory effect may be difficult to sign ex ante; firms with power may be able to sell more goods, but Fisher-Vanden, Mansur and Wang (2015) argue that firms may also substitute for unreliable power supply by purchasing materials inputs that embody more energy use.

on business outcomes. Nevertheless although our instrumental variables specifications should be interpreted with some caution, the patterns we observe in both OLS and IV estimates suggest that there may be significant benefits (higher profits) to businesses from improvements in the supply of power.

Importantly, the widespread prevalence of electricity theft and non-payment in Bihar (as in most of India and many developing countries), means that simply observing consumer willingness to pay for electricity may not be sufficient to conclude that consumers do not benefit from power or indeed value it. We observe that the utility fails to collect on all its dues even in the case of consumers who have signed up to buy power at prevailing tariffs and are legally speaking, violating the terms of their contract with the utility by not paying their bills. In this context it is difficult to infer the value of electricity from consumer payment behavior. Our results suggest that further work identifying the impacts of power supply on directly measured household and business outcomes may be very valuable in helping us understand the benefits and costs associated with expanding the grid, subsidizing tariffs, or increasing hours of supply in developing countries.

References

Allcott, Hunt, Allan Collard-Wexler, and Stephen D O'Connell. 2016. "How do electricity shortages affect industry? Evidence from India." *American Economic Review*, 106(3): 587–624.

Asher, Sam, and Paul Novosad. 2020. "Rural roads and local economic development." *American Economic Review*, 110(3): 797–823.

Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The miracle of microfinance? Evidence from a randomized evaluation." *American Economic Journal: Applied Economics*, 7(1): 22–53.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020*a*. "The consequences of treating electricity as a right." *Journal of Economic Perspectives*, 34(1): 145–69.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020*b*. "Demand for Electricity on the Global Electrification Frontier." *Mimeo*.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2008. "Returns to capital in microenterprises: evidence from a field experiment." *The quarterly journal of Economics*, 123(4): 1329–1372.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2009. "Are women more credit constrained? Experimental evidence on gender and microenterprise returns." *American Economic Journal: Applied Economics*, 1(3): 1–32.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2012. "One-time transfers of cash or capital have long-lasting effects on microenterprises in Sri Lanka." *Science*, 335(6071): 962–966.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2013. "The demand for, and consequences of, formalization among informal firms in Sri Lanka." *American Economic Journal: Applied Economics*, 5(2): 122–50.

Field, Erica, Seema Jayachandran, and Rohini Pande. 2010. "Do traditional institutions constrain female entrepreneurship? A field experiment on business training in India." *American Economic Review*, 100(2): 125–29.

Fisher-Vanden, Karen, Erin T Mansur, and Qiong Juliana Wang. 2015. "Electricity shortages and firm productivity: evidence from China's industrial firms." *Journal of Development Economics*, 114: 172–188.

Hardy, Morgan, and Jamie McCasland. 2019. "Lights Off, Lights On: The Effects of Electricity Shortages on Small Firms." *World Bank Economic Review*, lhz028.

IEA. 2020. "Access to electricity – SDG7: Data and Projections – Analysis."

Karlan, Dean, Ryan Knight, and Christopher Udry. 2015. "Consulting and capital experiments with microenterprise tailors in Ghana." *Journal of Economic Behavior & Organization*, 118: 281–302.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020*a*. "Does household electrification supercharge economic development?" *Journal of Economic Perspectives*, 34(1): 122–44.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020*b*. "Experimental evidence on the economics of rural electrification." *Journal of Political Economy*, 128(4): 1523–1565.

Lipscomb, Molly, A Mushfiq Mobarak, and Tania Barham. 2013. "Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil." *American Economic Journal: Applied Economics*, 5(2): 200–231.

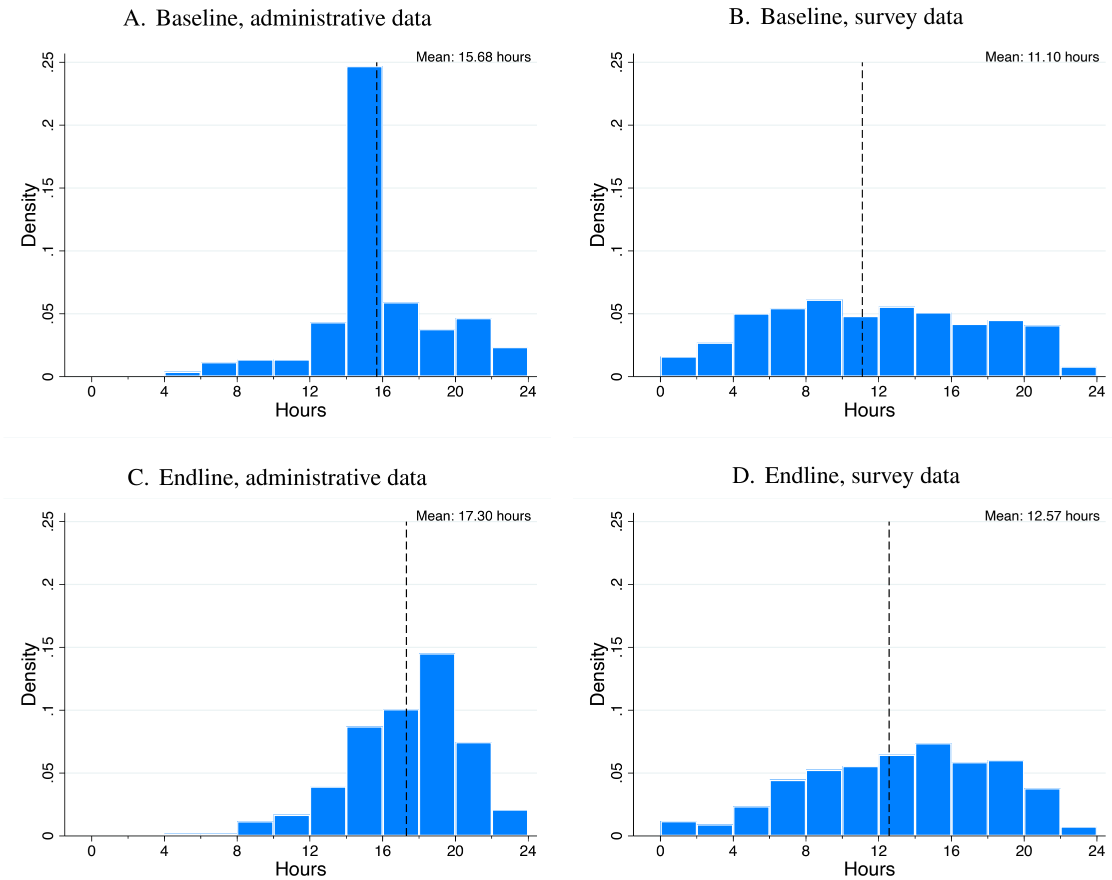
Ministry of Power. 2013. "Continuation of Rajiv Gandhi Grameen Vidyutikaran Yojana in 12th Plan."

Ministry of Power. 2015. "Prime Minister to Launch Deendayal Upadhyaya Gram Jyoti Yojana in Patna."

Ministry of Power. 2021. “SAUBHAGYA completes FOUR years of successful implementation.”

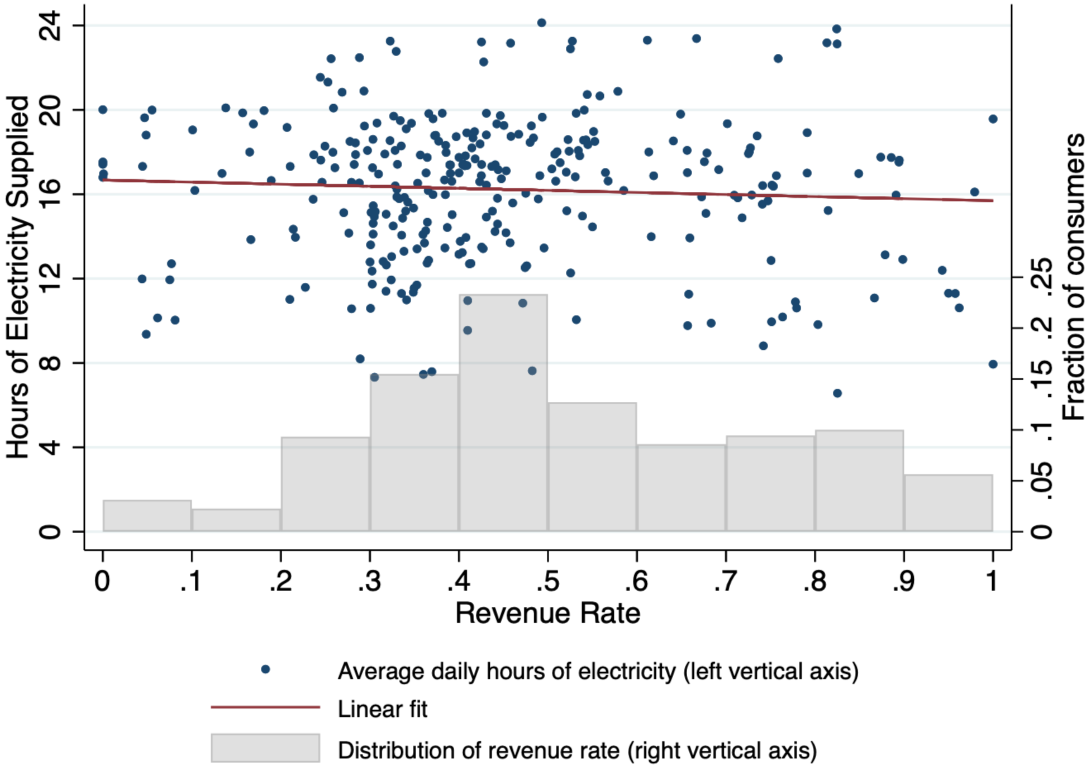
8 Figures

Figure 1: Daily hours of power supply



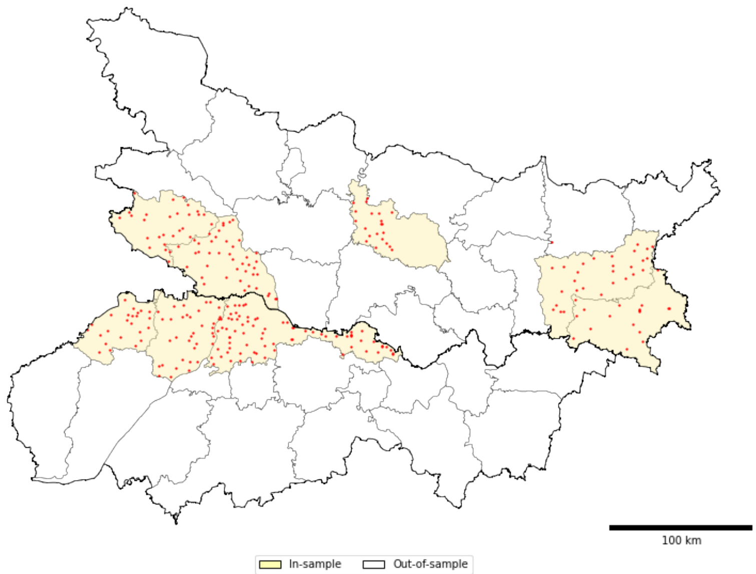
The histograms show the distribution of hours of power supply for businesses in the baseline survey (top row) and the endline survey (bottom row). The left-hand column shows the distribution of supply hours on the grid from administrative data on feeder log books. The right-hand column shows the distribution of supply hours from survey data, in response to the question "Please specify how many hours you received electricity each day on average over the last month?". The survey data shows the distributions only for businesses that reported having an electric connection from the grid.

Figure 2: Power supply vs Revenue Rate



This figure displays the relationship between the hours supplied and revenue rate for each feeder prior to treatment. The revenue rate for each month is calculated by dividing the revenue by the energy supplied times the price. The revenue rate, hours of electricity supplied, and number of consumers per feeder are then averaged over all months in the pre-period. Each point on the scatterplot represents such an average. Revenue rate and hours of electricity supplied are residualized by the indicators south and rural to account for differences in supplies between North and South regions, and rural and urban areas. Therefore, the blue scatter points should be interpreted as the equivalent revenue rate and hours of electricity supplied if a feeder is in an urban area in North Bihar. The red line plots the result of a simple linear regression of the hours of supply on the revenue rate. The grey bars represent the average fraction of consumers across each bin of revenue rates. Units for the hours supplied are given on the left axis, while units for the proportion of consumers in each bin are shown on the right axis.

Figure 3: Survey sample map

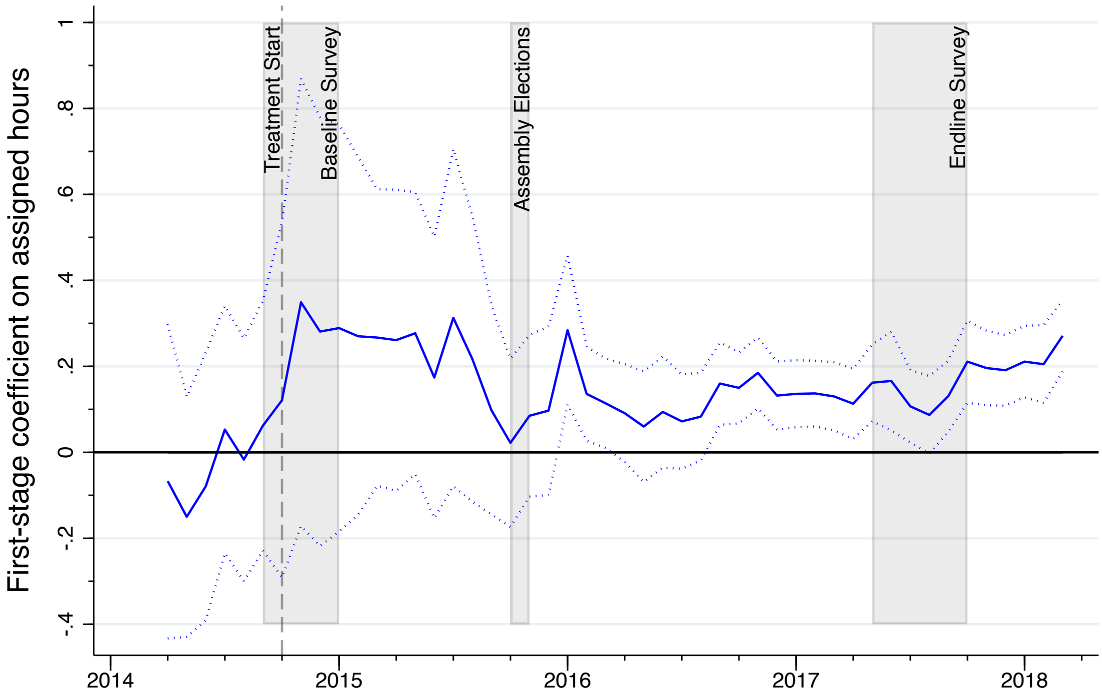


Panel A: Survey sample map

Panel B: Survey sample map

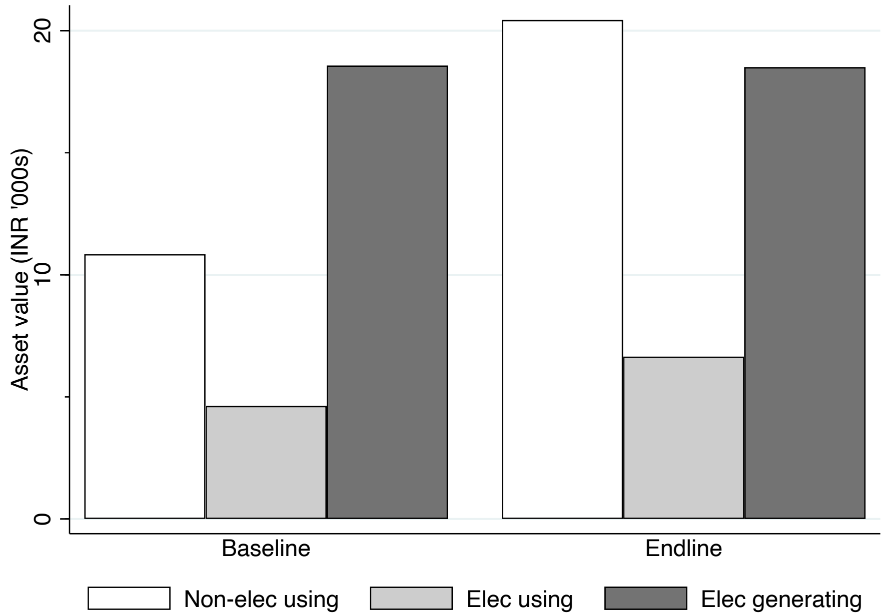
The figures show the location of firms sampled for the business survey. We sampled one market per feeder, picking markets with probability proportional to size. Within a selected market, we sampled up to 20 retail and service shops, and up to 20 manufacturing shops. In Panel A, the red dots on the graph indicate the mean latitude and longitude coordinates of businesses in each market. The bold dark lines represent North and South Bihar divided by the river Ganges. Panel B shows an example of the location of businesses we surveyed within a given market (Satjora).

Figure 4: First stage over time



The figure shows monthly coefficients from a regression of actual supply hours for treatment feeders on their assigned hours as in Table 3. Prior to treatment start, a supply schedule was not implemented. The assigned hours is constructed using the same assignment rule prior to the treatment assignment as afterwards. In each month, the coefficient can be interpreted as the change in supply for a one hour increase in assigned hours. Under perfect compliance the value would be 1.0, and with no compliance we would expect coefficients statistically indistinguishable from zero. The evidence suggests partial compliance. The regression includes month fixed effects separately for each discom. The dashed line shows 95 % confidence intervals.

Figure 5: Asset value in baseline and endline



This figure displays the average value in thousand INRs of non-electricity using assets (white), electricity using assets (light gray), and electricity generating assets (dark gray) of businesses in our baseline and endline surveys.

9 Tables

Table 1: Revenue-linked supply scheme assignment rule

	$North_i = 1$ (North)		$North_i = 0$ (South)	
Bin_{i0}	$Urban_i = 0$ (Rural)	$Urban_i = 1$ (Urban)	$Urban_i = 0$ (Rural)	$Urban_i = 1$ (Urban)
	$HoursAssigned_{i0} =$			
1	12	12	14	16
2	14	15	16	18
3	16	18	18	20
4	18	21	20	22
5	20	24	22	24

Assigned hours are increasing in the bin classification. The level of supply varies between rural and urban settings and across utilities because the experiment was designed to keep average outage hours identical to the pre-treatment status quo. After November 2017, the supply schedule was increased in rural areas of North Bihar by 2 hours. After August 2016, the supply schedule was increased in both urban and rural areas of South Bihar by 4 hours.

Table 2: Summary statistics: survey data

	Mean (1)	Std. Dev. (2)	Min. (3)	P25 (4)	P50 (5)	P75 (6)	Max. (7)	N (8)
Business sectors								
Business is manufacturing (=1)	0.13	0.33	0.00	0.00	0.00	0.00	1.00	6970
Business is service (=1)	0.44	0.50	0.00	0.00	0.00	1.00	1.00	6970
Business is retail (=1)	0.44	0.50	0.00	0.00	0.00	1.00	1.00	6970
Monthly profits (INR)	4539	8842	0	1200	3000	5000	400000	6342
Monthly revenue (INR)	21381	67233	0	5000	10000	20000	2000000	6740
Labor								
Employment	1.61	1.20	1	1	1	2	28	3536
Wage bill (INR per month)	6454	6849	50	4000	4000	8000	231000	2945
Labor days (per month)	42	33	1	25	26	50	840	2945
Labor wage (INR per day)	162	227	1	120	160	160	6000	2945
Capital								
Electricity-using capital (INR)	2493	14428	0	0	10	500	750010	6973
Electricity-generating capital (INR)	2173	11994	0	0	0	0	600000	6973
Non-electricity capital (INR)	10323	40031	0	1200	3000	8050	2514900	6973
Materials (INR)	55386	357800	0	1250	8000	40000	25000000	6973
Monthly rent imputed (INR)	795	1316	1	400	707	813	57293	6676
Monthly rent unimputed (INR)	748	1040	1	300	500	1000	25000	4176
Monthly energy expenditure imputed (INR)	1267	1752	0	250	750	1439	21302	3561
Electricity								
Connected to electricity grid (=1)	0.58	0.49	0.00	0.00	1.00	1.00	1.00	3861
Hours of electricity supply	14.81	3.68	4.55	13.48	14.96	16.68	22.98	3511
Number of bulbs own	1.62	24.91	0.00	0.00	0.00	2.00	2000.00	6973

This table presents summary statistics on variables obtained from all businesses in our baseline survey. The observation counts differ across variables because not all businesses responded to every question on the survey.

Table 3: Simple first stage (controls added)

	Hours of supply: before treatment				Hours of supply: during treatment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HoursAssigned_t	-0.0302	0.0346			0.199^{***}	0.216^{***}		
	(0.109)	(0.105)			(0.0560)	(0.0566)		
HoursAssigned_0			0.0522	0.0438			0.153^{***}	0.147^{**}
			(0.0907)	(0.0815)			(0.0587)	(0.0588)
Month FE		Yes		Yes		Yes		Yes
F-stat (excluded instruments)	0.08	0.11	0.33	0.29	12.65	14.65	6.76	6.29
Mean dep. variable	16.78	16.78	16.85	16.85	15.92	15.92	15.91	15.91
Month T	48	48	46	46	42	42	42	42
Panel N	319	319	321	321	326	326	321	321
Feeder-month N	2522	2522	4448	4448	8270	8270	8228	8228
R^2	0.29	0.49	0.28	0.48	0.38	0.48	0.38	0.48

This table presents the results from a first stage regression of the hours of supply as reported from the administrative data on the assigned hours for the experiment. The first four columns use hours of supply before the scheme was implemented as a balance check, while the last four columns use hours supplied during the treatment. Columns 1, 2, 5, and 6 use the hours assigned at the given month as the independent variable, while columns 3, 4, 7, and 8 use the initial assigned hours. Month fixed effects are included when indicated. Robust standard errors clustered at the feeder-level are shown in parentheses with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Effect of RLSS treatment assignment on revenues and cost recovery

	Energy supply cost (INR ’000)		Net revenue (INR ’000)		Revenue rate (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
$TreatmentSchedule \times Post$	685.5	-276.7	-513.1	175.5	0.0115	0.0346
	(425.6)	(273.4)	(365.3)	(320.4)	(0.0535)	(0.0467)
$TreatmentSchedule$	-628.1		571.7*		-0.0573	
	(390.5)		(311.1)		(0.0604)	
Feeder FE		Yes		Yes		Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. variable	3662	3662	-3049	-3049	0.37	0.37
Month T	48	48	48	48	48	48
Panel N	330	330	326	326	326	326
Feeder-Month N	9793	9793	8310	8310	8281	8281
R^2	0.03	0.68	0.03	0.64	0.02	0.50

This table presents the results from a difference-in-differences regression of three outcomes–energy supply cost in thousand INR (columns 1-2), net revenue in thousand INR (columns 3-4), and revenue rate (columns 5-6)–using various specifications. Energy supply cost is calculated by multiplying energy consumption with average pooled power purchase cost for the distribution companies at the time of the experiment. In columns 1, 3, and 5, we use an indicator for being assigned to treatment instead of feeder fixed effects, and we include feeder fixed effects in columns 2, 4, and 6. We use month fixed effects instead of a post indicator for all columns.

Table 5: Effect of hours of supply on revenues and cost recovery (TSLS)

	Energy supply cost (INR '000)		Net revenue (INR '000)		Revenue rate (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Hours of supply	-164.1	-17.75	66.76	-14.86	-0.0341	-0.141**
	(316.2)	(236.0)	(252.9)	(182.0)	(0.0209)	(0.0582)
Anderson-Rubin (1949) p-value	0.54	0.72	0.29	0.70	0.10	0.28
Moreira (2003) CLR p-value	0.48	0.94	0.75	0.89	0.02	0.40
Region × urban × bin	Yes		Yes		Yes	
Feeder FE		Yes		Yes		Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald (1993) F-stat	22.00	4.68	23.04	3.11	22.92	3.11
Kleibergen-Paap (2006) F-stat	4.42	3.80	4.33	5.70	4.32	5.69
Montiel-Pflueger (2013) effective F-stat	2.04	1.16	2.21	0.94	2.20	0.94
Critical value for effective F-stat	15.56	16.01	15.69	16.67	15.69	16.67
Mean dep. variable	3671	3671	-3052	-3052	0.37	0.37
Month T	48	48	48	48	48	48
Panel N	328	328	326	326	326	326
Feeder-month N	9747	9747	8295	8295	8281	8281
R^2	0.07	0.68	0.10	0.64	0.11	0.44

This table presents the results from an IV regression of three outcomes–energy supply cost in thousand INR (columns 1-2), net revenue in thousand INR (columns 3-4), and revenue rate (columns 5-6), which is instrumented using region × urban × bin indicators. Energy supply cost is calculated by multiplying energy consumption with average pooled power purchase cost for the distribution companies at the time of the experiment. Columns 1, 3, and 5 include these as control variables, while columns 2, 4, and 6 use feeder fixed effects instead. Month fixed effects are included in all 6 columns.

Table 6: Electricity supply and business profits

	TSLS				OLS			
	All	Retail	Service	Manufact-uring	All	Retail	Service	Manufact-uring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Firm Level (Profits in INR)							
Hours of supply	297.4**	152.8	286.9**	671.5**	79.81**	6.758	128.5***	118.4
	(145.8)	(189.9)	(145.2)	(261.1)	(31.55)	(51.50)	(33.83)	(101.3)
	Panel B: Feeder Level (Profits in INR '000)							
Hours of supply	153.9**	53.66	39.27**	15.93**	41.31**	2.373	17.59***	2.809
	(75.46)	(66.71)	(19.87)	(6.194)	(16.33)	(18.09)	(4.630)	(2.404)
Anderson-Rubin (1949) p-value	0.67	0.49	0.71	0.22				
Moreira (2003) CLR p-value	0.32	0.88	0.39	0.29				
Cragg-Donald (1993) F-stat	19.27	9.44	7.91	5.38				
Kleibergen-Paap (2006) F-stat	4.04	4.27	4.04	10.93				
Montiel-Pflueger (2013) effective F-stat	1.49	1.73	1.19	2.81				
Critical value for effective F-stat	15.89	15.52	16.08	16.55				
Avg base dep. var.	4138	4539	3637	4923	4138	4539	3637	4923
Avg end dep. var.	4521	4868	4063	5325	4521	4868	4063	5325
Avg cens firm / feed	517.66	351.22	136.87	23.72	517.66	351.22	136.87	23.72
Feeder obs.	283	283	283	275	283	283	283	275
Firm obs.	4316	1724	2120	471	4316	1724	2120	471
R^2	0.08	0.10	0.11	0.03	0.10	0.10	0.12	0.09

Panel A reports the results of an IV regression of endline firm profits in INR on the hours of supply from the feeder instrumented by treatment $\times$ region $\times$ urban $\times$ bin indicators. In all columns, the baseline dependent variable and the region $\times$ urban $\times$ bin indicators are included as controls. Panel B reports the feeder level equivalent results of panel A. We multiply the Panel A coefficient and standard deviation of hours supplied by the average number of firms per feeder in the baseline census. Columns 1 and 5 use all firms in our survey, while the other columns restrict the sample to the denoted sectors. We trim the baseline and endline production inputs observations at the 0.5% and 99.5% cutoff to account for outliers in profits; revenue observations are trimmed at the top 99%. Robust standard errors clustered at the feeder-level are shown in parentheses with statistical significance indicated by $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 7: Electricity supply and business inputs

	Labor			Capital				Materials	Land
	Days	Wage Bill	Wage	Total	Elec using	Non-elec using	Elec generating	Inventory	Rent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Hours of supply	1.659*	486.6***	5.149***	1738.2**	530.9***	776.1	64.55	828.3	54.94**
	(0.969)	(174.6)	(1.387)	(725.1)	(157.4)	(527.8)	(152.6)	(1712.5)	(26.95)
Anderson-Rubin (1949) p-value	0.22	0.54	0.32	0.16	0.12	0.16	0.72	0.22	0.41
Moreira (2003) CLR p-value	0.23	0.18	0.10	0.24	0.03	0.25	0.76	0.63	0.15
Cragg-Donald (1993) F-stat	9.23	9.10	8.70	21.65	21.42	21.47	21.53	21.45	9.62
Kleibergen-Paap (2006) F-stat	4.97	5.04	5.98	4.46	4.47	4.44	4.48	4.45	4.34
Montiel-Pflueger (2013) effective F-stat	1.54	1.50	1.48	1.47	1.45	1.45	1.45	1.45	1.16
Critical value for effective F-stat	16.68	16.72	16.62	16.16	16.19	16.19	16.22	16.21	15.60
Avg base dep. var.	42	6449	152	10574	1690	8556	1659	39825	630
Avg end dep. var.	41	6934	163	20300	3311	16245	1995	42073	810
Avg cens firm / feed	242	242	242	259	259	259	259	259	240
Feeder obs.	1911	1913	1916	4948	4956	4947	4958	4967	2616
Firm obs.	0.11	0.18	0.21	0.10	0.19	0.07	0.18	0.22	0.43

This table reports the results of an IV regression of endline firm inputs on the hours of electricity supply from the feeder instrumented by region × urban × bin indicators. In all columns, the baseline dependent variable and the region × urban × bin indicators are included as controls. Column 1 reports the effect on total days worked, column 2 reports the effect on total earnings, and column 3 reports the effect on wages. Columns 4-7 report the effect on the value of all capital owned by the firm, the electricity using capital only, the non-electricity using capital only, and the electricity generating capital, respectively. Column 8 reports the effect on the value of the inventory, while column 9 reports the effect on monthly rent. We trim the baseline and endline production inputs observations at the 0.5% and 99.5% cutoff to account for outliers. Robust standard errors clustered at the feeder-level are shown in parenthesis with statistical significance indicated by $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

A Appendix: Data

A.1 Parent and Child Feeders

As new customers connect to grid, existing "parent" feeders can split off into multiple "child" feeders. We aggregate the child feeders at the parent feeder level if the split occurs after treatment starts for the parent feeder. When aggregating at the parent feeder level, we treat the main variables in the following manner:

- Energy consumption: sum of child feeder energy consumption.
- Revenue collection: sum of child feeder revenue collection.
- Cost injection: sum of child feeder cost injection.
- Revenue rate: aggregated revenue collection / aggregated cost injection
- Assigned Wave: use the assigned wave of parent feeder.
- Post: parent and child feeder have the same assignment wave so post is the same.
- Treatment assignment: parent and child feeder have the same treatment assignment.
- Initial bin assignment: Use parent feeder initial bin assignment.
- Assigned hours: weighted average of child feeder assigned hours by cost injection. When cost injection is missing, we interpolate using nearest values.
- Hours: weighted average of child feeder supply average by cost injection. When cost injection is missing, we interpolate using nearest values.

Table A1: RLSS marketing summary

Marketing Channel	Total Distribution Count	People Reached	People $\times$ Month Reached	Total Cost	Duration
SMS notifications	1,592,083	171,595	1,592,083	191,049.96	Oct. 2016 - Mar. 2018
Bill insert	7,091,247	254,957	7,091,247	2,198,286.8	Mar. 2015 - Jul. 2017
Announcements	607			303,500	Apr. 2015 - Apr. 2017
Posters	5,720			74,360	Apr. 2016 - Jan. 2017
Total	8,689,657			2,767,196.76	

This table presents the total distribution count, unique people reached, total people reached over months, total cost, and duration of the four marketing media. SMS notification statistics are based on customers that were given treatment assignments for the SMS intervention in October 2016 and September 2017. We use the monthly cost per unit of SMS notification 0.12 Rs to calculate cost. Bill inserts were suspended during the election period from August to December 2015. The bill inserts began again in March 2016 and ended in July 2017. No bill inserts were printed in April 2017 due to unavailability of calendar design. We used the monthly cost per unit of bill insert 0.31 Rs to calculate cost. Based on the August 2016 report, for North Bihar, number of feeders with completed announcements was 17 and number of posters placed was 354. For South Bihar, number of feeders with completed announcements was 14 and number of posters placed was 218 for South Bihar. We assumed that this is the average number of announcements and posters placed for every month. Moreover, we assumed that only one announcement is made per feeder each month. We used the monthly cost per feeder for announcements and posters, which are 500 and 130 Rs respectively, to calculate cost. We omitted the people reached and people $\times$ month reached for announcements and posters because we do not have data on how many people received information from such marketing channels.

Table A2: Administrative data balance table

	Treatment	Control	Difference
Hours of supply	16.7	16.7	-0.070
	[4.25]	[4.36]	(0.48)
	164	164	328
Revenue	462294.9	471291.5	-8996.6
	[533768.1]	[559688.6]	(59235.0)
	170	171	341
Energy injection	643.3	699.9	-56.6
	[496.9]	[550.4]	(58.8)
	156	163	319
Urban	0.24	0.26	-0.028
	[0.43]	[0.44]	(0.047)
	170	171	341
Total consumers	1512.8	1684.1	-171.3
	[1884.7]	[2046.4]	(213.1)
	170	171	341
Domestic consumers	1021.4	1102.2	-80.8
	[1438.0]	[1395.2]	(153.4)
	170	171	341
Kutir Jyoti consumers	326.5	387.2	-60.7
	[465.1]	[625.3]	(59.7)
	170	171	341

This table tests the balance of key variables across feeders in the treatment and control groups in the administrative data in the pre-period. Since the dataset is a panel, we take the mean of all observations across months in the pre-period before conducting the balance tests. Robust standard errors are shown in brackets with statistical significance indicated by $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A3: Survey data balance table

	Treatment	Control	Difference
Business is manufacturing (=1)	0.11	0.13	-0.014
	[0.32]	[0.33]	(0.013)
	2917	3252	6169
Business is service (=1)	0.45	0.43	0.012
	[0.50]	[0.50]	(0.016)
	2917	3252	6169
Business is retail (=1)	0.44	0.44	0.0027
	[0.50]	[0.50]	(0.014)
	2917	3252	6169
Monthly profits	4320.0	4650.4	-330.4
	[5978.2]	[11209.9]	(314.9)
	2670	2922	5592
Monthly revenue	21894.8	19559.3	2335.5
	[71774.6]	[53687.0]	(1715.1)
	2829	3125	5954
Employment	1.53	1.64	-0.11**
	[1.08]	[1.30]	(0.047)
	1462	1624	3086
Wage bill (per month)	5990.6	6580.0	-589.4*
	[4865.8]	[8304.9]	(314.3)
	1224	1359	2583
Labor days (per month)	39.2	42.1	-2.94**
	[28.0]	[37.4]	(1.45)
	1224	1359	2583
Labor wage (per day)	165.7	159.8	5.93
	[270.5]	[211.2]	(9.91)
	1224	1359	2583
Electricity-using capital	2716.3	2047.5	668.8*
	[19256.6]	[7653.8]	(378.2)
	2918	3254	6172
Electricity-generating capital	1964.9	2395.6	-430.6
	[9812.0]	[14289.0]	(358.6)
	2918	3254	6172
Non-electricity capital	10359.8	9855.8	504.0
	[51374.4]	[26727.9]	(985.4)
	2918	3254	6172
Materials	58972.4	48056.3	10916.2
	[512242.7]	[171650.7]	(10433.7)
	2918	3254	6172

Monthly rent	690.0	677.9	12.2
	[885.1]	[958.9]	(66.2)
	1736	1948	3684
Connected to electricity grid (=1)	0.55	0.56	-0.013
	[0.50]	[0.50]	(0.046)
	1538	1771	3309
Hours of electricity supply	14.5	15.1	-0.61
	[3.61]	[3.90]	(0.61)
	1569	1765	3334
Number of bulbs own	1.24	1.27	-0.030
	[8.70]	[5.08]	(0.19)
	2918	3254	6172

Table A4: Summary statistics: survey data by sectors

	All	Retail	Service	Manufacturing
Business sectors				
Business is retail (=1)	0.44	1.00	0.00	0.00
Business is service (=1)	0.44	0.00	1.00	0.00
Business is manufacturing (=1)	0.13	0.00	0.00	1.00
Monthly profits (INR)	4539	4935	3852	5570
Monthly revenue (INR)	21381	28844	13079	24493
Labor				
Employment	1.61	1.37	1.63	2.16
Wage bill (INR per month)	6454	5176	6046	10323
Labor days (per month)	42	35	41	56
Labor wage (INR per day)	162	152	148	222
Capital				
Electricity-using capital (INR)	2493	1337	2730	5693
Electricity-generating capital (INR)	2173	431	2168	8235
Non-electricity capital (INR)	10323	11700	8327	12535
Materials (INR)	55386	94353	18575	47775
Monthly rent imputed (INR)	795	808	697	1081
Monthly rent unimputed (INR)	748	791	624	1046
Monthly energy expenditure imputed (INR)	1267	726	1374	2716
Electricity				
Connected to electricity grid (=1)	0.58	0.62	0.57	0.47
Hours of electricity supply	14.81	14.86	14.63	15.21
Number of bulbs own	1.62	1.96	1.32	1.50

This table presents mean values of variables obtained by businesses in our baseline survey. The first column presents means across all businesses in the survey, while the next three columns presents means for businesses within the retail, service, and manufacturing sectors.

A.2 Business Assets

We classisifed business assets in the survey into electricity using and non-electricity using assets.

- Electricity using assets: airconditioner, aircooler, battery, bulb, cardswipe, cfl, coldstorage, copier_tools, desktop, drill, elecgrill, eleciron, elecmill, elecpurifier, elecsaw, elecweight, electronic, emerglight, emerg_tools, fan, genset, genset_tools,grindingequip, hairdrier, insect-catcher, inverter, laptop, lathe, led, mill_tools, mobile, motor, oven, photostat, polishmachine, printer, radio, refrigerator, roomheater, scanner, soundsys, stabilizer, television, tubelight, weldingequip, weldingmachine.
- Non-electricity using assets: airtank_tools, autotool, battery_tools, bicycletool, blacksmith-tool, bottlemachine, cage, calculator, camera, carpentarytool, clock, crate, cutter, cutting-tool, drill_tools, electrictool, gascooker, gascylinder, generator, glasscontainer, grinder, hair-dress, hairdresstool, kiosk, ladders, lamp, measuretape, mediacalequip, medicaltool, metal-container, metalware, mirror, mobile_tools, noneleciron, nutcracker, plasticcontainer, plas-ticware, pump, purifier, rope, sewing, shoetool, shovel, stove, solar_tools, tape, torch, tyre, utensil, weight, woodcontainer, auto, barrow, bike, car, cart, cycle, lorry, pedalrickshaw, rick-shaw, tractor, van, almirah, bed, bench, chair, counter, desk, dresser, dresstable, ladder, met-box, shelve, showcase, sofa, stool, woodbox, woodframe.

Table A5: Most common assets: baseline

Non-electrical (% Owning)	Electrical (% Owning)	Generating (% Owning)
	Panel A: Retail	
cycle (33.8%)	bulb (28.2%)	generator (17.3%)
chair (31.5%)	fan (21.3%)	solar (3.6%)
showcase (30.8%)	tubelight (21.0%)	
weight (30.4%)	elecweight (6.8%)	
desk (28.8%)	refrigerator (3.2%)	
calculator (27.3%)	laptop (2.2%)	
clock (24.6%)	printer (1.9%)	
woodbox (21.0%)	desktop (1.2%)	
shelve (17.7%)	coldstorage (0.4%)	
bike (11.2%)	battery (0.4%)	
	Panel B: Service	
desk (42.0%)	bulb (24.8%)	generator (18.0%)
chair (41.9%)	fan (16.9%)	solar (1.7%)
cycle (35.1%)	tubelight (13.1%)	
showcase (21.0%)	printer (3.9%)	
clock (16.6%)	desktop (3.3%)	
woodbox (13.4%)	laptop (2.8%)	
sewing (12.2%)	scanner (1.6%)	
bike (9.1%)	refrigerator (1.5%)	
bicycletool (8.6%)	eleciron (0.6%)	
shelve (8.1%)	genset (0.5%)	
	Panel C: Manufacturing	
cycle (36.8%)	bulb (35.4%)	generator (30.4%)
chair (34.5%)	fan (9.8%)	solar (0.3%)
carpentarytool (29.9%)	drill (9.1%)	
desk (27.5%)	elecweight (7.3%)	
weight (25.8%)	elecsaw (5.5%)	
woodbox (13.5%)	tubelight (3.3%)	
clock (13.4%)	genset (3.3%)	
bike (12.0%)	weldingequip (1.6%)	
calculator (11.0%)	elecmill (1.3%)	
metalcontainer (10.3%)	motor (1.1%)	

This table displays the most frequently owned electricity using, non-electricity using, and electricity generating assets as reported by businesses in the baseline survey. Panel A focuses on retail firms, panel B focuses on service firms, and panel C focuses on manufacturing firms.

Table A6: Most common assets: endline

Non-electrical (% Owning)	Electrical (% Owning)	Generating (% Owning)
	Panel A: Retail	
shelve (60.4%)	bulb (68.8%)	generator (20.2%)
counter (54.8%)	fan (54.2%)	solar (11.0%)
chair (41.8%)	inverter (20.4%)	
calculator (40.5%)	elecweight (17.3%)	
weight (39.2%)	emergtools (7.1%)	
cycle (37.3%)	refrigerator (6.5%)	
cutter (36.4%)	tubelight (6.3%)	
bench (32.7%)	printer (1.9%)	
stool (31.0%)	laptop (1.9%)	
bike (27.7%)	desktop (1.6%)	
	Panel B: Service	
bench (46.9%)	bulb (60.0%)	generator (24.6%)
counter (45.4%)	fan (43.5%)	solar (7.1%)
cycle (44.1%)	inverter (19.5%)	
cutter (42.6%)	electronic (8.0%)	
chair (40.9%)	refrigerator (7.0%)	
stool (28.8%)	printer (6.3%)	
utensil (28.7%)	elecweight (5.7%)	
shelve (26.1%)	tubelight (5.7%)	
desk (25.6%)	laptop (5.1%)	
clock (24.2%)	desktop (4.4%)	
	Panel C: Manufacturing	
cycle (44.6%)	bulb (66.7%)	generator (74.1%)
chair (43.1%)	fan (41.7%)	solar (4.4%)
cutter (38.8%)	weldingmachine (19.9%)	
bench (38.8%)	elecweight (18.4%)	
tape (38.2%)	drill (18.1%)	
carpentarytool (37.9%)	elecsaw (18.0%)	
stool (31.6%)	inverter (12.6%)	
bed (31.4%)	electronic (7.0%)	
bike (30.9%)	tubelight (3.0%)	
weight (28.3%)	refrigerator (2.4%)	

This table displays the most frequently owned electricity using, non-electricity using, and electricity generating assets as reported by businesses in the endline survey. Panel A focuses on retail firms, panel B focuses on service firms, and panel C focuses on manufacturing firms.

Table A7: Most common business types: baseline and endline

Baseline (Count)	Endline (Count)
Panel A: Retail	
Departmental Store (595)	Departmental Store (529)
Paan/Cigarette Shop (578)	General Store (441)
General Store (415)	Drug Store (245)
Garment Store (304)	Garment Store (237)
Drug Store (260)	Paan/Cigarette Shop (196)
Sweets Shop (255)	Cosmetics Shop (158)
Mobile Shop (210)	Mobile Shop (150)
Cosmetics Shop (185)	Hardware Shop (145)
Hardware Shop (160)	Others (112)
Agriculture Seed/Chemical Shop (133)	Electronics Store (103)
Panel B: Service	
Beauty Parlour/Haircut Salon (292)	Paan/Tobacco Processing Shop (329)
Tailor (221)	Hotel (253)
Bicycle Repair (201)	Beauty Parlour/Haircut Salon (248)
Tea stall/Cold-drink Shop (198)	Tea stall/Cold-drink Shop (222)
Hotel (177)	Tailor (203)
Private Clinic (173)	Bicycle Repair (193)
Electronic Repair (163)	Private Clinic (164)
Automobile repair (108)	Metal Processing (163)
Metal Processing (70)	Grain Processing (150)
Restaurant/ Dhaba (53)	Wood Processing (124)
Panel C: Manufacturing	
Wood workshop (481)	Wood workshop (294)
Metal workshop (357)	Metal workshop (218)
Mill (300)	Sweets/Confectionery Production (41)
Sweets/Confectionery Production (27)	Mill (31)
Biscuit Factory (14)	Jewellery Making (25)
Jewellery Making (3)	Others (20)
Pottery (2)	Blacksmith (13)
Textile Industry (1)	Biscuit Factory (11)
Ice Factory (1)	Ice Factory (1)
Pillar Making (1)	Pillar Making (1)

This table displays the most frequent business types for each of the three categories as reported in the baseline (left) and endline (right) survey.

Table A8: Entry and Exit

	(1) All	(2) Retail	(3) Service	(4) Manufacturing
	Panel A: Net Entry (Normalized Per Feeder)			
Hours of supply	-0.00699	-0.0377	0.0433	-0.0217
	(0.0282)	(0.0325)	(0.0374)	(0.0597)
Mean dep. variable	0.18	0.11	0.45	-1.29
Feeder obs.	238	238	238	238
R^2	0.07	0.03	0.01	0.14
	Panel B: Firm-level Entry Indicator			
Hours of supply	-0.00135	-0.000239	-0.00447	0.0105
	(0.00683)	(0.00687)	(0.00726)	(0.0147)
Mean dep. variable	0.25	0.25	0.24	0.25
Firm obs.	149174	94780	51892	1094
R^2	0.00	0.00	0.00	0.03

This table reports the results of IV regressions of entry and exit decisions on hours of electricity supplied. We use region × urban × bin and treatment × region × urban × bin as instruments. Panel A reports the results for net entry. To calculate the net entry, we find the number of firms for each feeder in the baseline and endline censuses, then take the difference. Net entry is normalized by the average of the number of firms in the feeder in baseline and endline censuses. Panel B reports the results for an exit indicator for each firm in the census, which equals 1 if the firm was present in the endline census but not the baseline census. Column 1 includes all businesses in our sample, whereas columns 2-4 only include businesses in the sector indicated. Robust standard errors clustered at the feeder-level are shown in parenthesis with statistical significance indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: North Bihar: Cost and Revenue

	North Bihar: Cost and Revenue (Rs/kWh)		
Fiscal Year	Power Purchase Cost	Cost of Supply	Revenue Realization
2014 - 2015	3.88	6.13	4.57
2015 - 2016	4.15	6.07	4.32
2016 - 2017	4.25	5.62	4.03
2017 - 2018	4.22	7.07	6.97

This table reports the average power purchase costs, average cost of supply, and average revenue realization, based on Bihar Electrification Regulatory Commission Tariff Order of North Bihar Power Distribution Company Limited (NBPDCL). The average power purchase cost includes transmission charges. The average revenue realization excludes government subsidy.

Table A10: South Bihar: Cost and Revenue

	South Bihar: Cost and Revenue (Rs/kWh)		
Fiscal Year	Power Purchase Cost	Cost of Supply	Revenue Realization
2014 - 2015	4.22	7.07	6.97
2015 - 2016	4.18	6.31	4.87
2016 - 2017	4.25	5.85	4.60
2017 - 2018	4.21	7.55	7.27

This table reports the average power purchase costs, average cost of supply, and average revenue realization, based on Bihar Electrification Regulatory Commission Tariff Order of South Bihar Power Distribution Company Limited (SBPDCL). The average power purchase cost includes transmission charges. The average revenue realization excludes government subsidy.