Coping with Blackouts: Power Outages and Firm Choices

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ABSTRACT

Electricity is cited as one of the biggest impediments to firm growth in developing countries. In the World Bank Enterprise Survey (2006), 35.2% of Indian firms list electricity as the single biggest obstacle to business and report that power outages result in losses equivalent to 6.6% of annual sales. However, some businesses can adjust their means of production to cope with electricity shortages. The ability to re-optimize implies that electricity shortages may not necessarily decrease output because some firms will respond by changing their production processes and demand for inputs. In this paper, I study the consequences of inter-industry heterogeneity in adaptation to electricity shortages on a firm's output and profits. I use meteorological satellite data to construct an objective measure for the frequency of power outages. My results indicate that the impact of power outages varies by type of industry: an increase in the frequency of power outages lowers the output and profits of only some electricity-intensive industries.

Keywords: Adaptation, Electricity, Firm Choices, Infrastructure

JEL: O18, D22

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1. Introduction

A vast and growing literature has shown that the provision of infrastructure results in improvements in economic indicators.[1] However, in some contexts, the absence of infrastructure is not a binding constraint. Rather, it is the quality of the infrastructure that is the barrier for economic growth. For example, Lipscomb et al. (2013) study the development effects of electrification in Brazil and find that by the year 2000 all of Brazil had been electrified. Yet researchers have a limited understanding of how poor quality infrastructure affects the decisions of firms and businesses. Profit maximizing firms do not simply absorb the costs and consequences of unreliable infrastructure without adjusting their means of production; they can alter their production strategy. The ability to re-optimize decisions may limit the adverse effects of poor infrastructure and create significant inter-industry heterogeneity in its impact. Therefore, improvements in the quality of infrastructure may have very different effects across industries, and as a result, an uneven impact on economic growth.

This paper studies the consequences of inter-industry heterogeneity (in technical possibilities) in adaptation to electricity shortages on firms' output and profits in India. Literature in this area assumes that power outages have a homogenous impact on electricity-intensive firms.[2] I show that there is an important, yet neglected, dimension of heterogeneity: adaptation to power outages varies significantly across industries. For my analysis, I strategically choose two major electricity-intensive industries in India that use different adaptation mechanisms to cope with power outages: rice and steel mills. I explicitly model the differences in adaptive capabilities of the two industries. Since rice mills have more adaptation mechanisms available to them, my model predicts that they are less adversely affected. On the empirical front, acquiring power outage data for all of India is a difficult task. I address this challenge by using meteorological satellite data to construct an objective measure for the frequency of power outages.[3] Consistent with the model's predictions, I find evidence that, unlike steel mills, rice mills are able to adjust to power outages by altering their production strategy. Consequently, increases in the frequency of power outages reduce the output and profits of steel mills but not rice mills. These findings have important implications for infrastructure policy: improvements in electricity supply will have very different effects across industries depending on the technical adaptation mechanisms available.

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[1]Key papers include Calderon et al. (2011), Dinkelman (2011), Donaldson (forthcoming), Jensen (2007), and Lipscomb et al. (2013).

[2]Key papers include Alby et al. (2013), Fisher-Vanden et al. (2012), and (Reinikka and Svensson (2002).

[3]Nightlights data have been used to study economic growth by Chen and Nordhous (2011), Henderson et al. (2012), and Kulkarni et al. (2011).

The Indian context is ideal for assessing my research question. Even though 91% of Indian villages had access to electricity by 2011 (Khandkar et al., 2012), the availability of reliable electricity remains a major challenge for India's industrial sector. In the World Bank Enterprise Survey (2006), 35.2% of Indian firms cite electricity as the single biggest obstacle to business. Electricity is a bigger problem for these firms than more commonly studied factors, such as tax rates, corruption, access to finance, and transportation.[4] Furthermore, India has never met its peak demand for electricity.[5] Since infrastructure development has not kept pace with the growing electricity needs of the consumers, demand-side management (power outages) is used to make up for electricity deficit. As a result, power outages are frequent. South Asian firms report experiencing an average of more than one outage a day. Indian firms report that a typical outage lasts for 3.1 hours and that outages result in losses equivalent to 6.6% of annual sales.[6]

I exploit variation in two attributes of the production process to empirically address my research question: (1) reliance on electricity for production and (2) adaptability of the production process to electricity shortage. To accomplish this, I strategically focus on three Indian industries: rice mills, steel mills, and brick kilns. Brick kilns, rice mills, and steel mills vary in their reliance on electricity and adaptability to power outages in the following manner: (1) Brick kilns do not use electricity for their production process and instead rely on either coal or wood to meet their energy needs. In comparison, both rice and steel mills are highly electricity-intensive industries. For most rice mills and the majority of steel mills all the different stages of production rely on electricity. (2) Rice and steel mills can use different adaptation mechanisms to cope with power outages despite being heavily dependent on electricity. While both rice and steel mills can adapt to power outages via generator adoption, rice mills can also adjust by switching to a more electricity-efficient technology and accelerating the production process: the machinery can be operated faster but at the expense of increased wastage of unprocessed rice (paddy).[7] As a result, rice mills are more adaptable to electricity shortage than steel mills.

Furthermore, both rice and steel mills are important industries for the Indian economy. Rice milling is the biggest grain processing industry in India in terms of output. Similarly,

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[4]See figure 2 for details.

[5]On average, India was unable to meet 12.7% of peak demand between 1997 and 2009 (Ministry of Power, India).

[6]Source: Enterprise Survey (World Bank).

[7]Using the electricity-efficient technology significiantly increases the cost for rice mills due to paddy wastage (in my data, paddy constitutes approximately 95% of the variable expenditure).

steel-making is also a major industry in India. The steel sector contributes 2% to India's GDP. In 2010, India produced 68.32 million tons crude steel and was ranked 4th largest steel producer in the world.

My model allows electricity-constrained firms to use two adaptation channels when deciding on optimal levels of material usage and capital holdings. The two adaptation channels are: (1) both rice and steel mills can install a generator (2) only rice mills can switch to a costly but electricity-efficient technology as power outages increase. The input and technological choices determine output and profits of firms. Since the adaptation mechanisms available to rice and steel mills are different, my model generates different predictions for the two industries as power outages become more frequent. As power outages increase, steel mills use less material, produce less output, and make lower profits. In contrast, the material usage and output of rice mills increases if they switch to the more electricity-efficient technology as power outages increase. At the point that rice mills switch between the two technologies, their profits remain unchanged.

Most empirical studies use self-reported measures of power outages since gathering actual outage data is difficult. Such self-reported measures can potentially be biased because firms that own generators are less likely to report power outages. I circumvent this problem by constructing a novel measure for the frequency of power outages using meteorological satellite data. I use two annual nightlights composites to construct my measure of power outages: the stable lights composite and the normalized visible lights composite. The stable lights composite contains the average luminosity at a location. In contrast, the normalized visible lights composite contains the normalized average luminosity (if a light is observed only 50% of the time then it is weighed down by 0.5). For a given location, the difference between the luminosity in these two composites is higher if the observed lighting is more variable. I use this variability in light intensity to measure power outages at the district-year level.

The input and output choices of firms depend on the business climate that they face. Therefore, my key empirical challenge is to control for variables outside my model that may influence both power outages and the business environment. For example, economic growth can be positively correlated with electricity shortages if infrastructure is not able to keep up with the growing demand for electricity. Similarly, local state capacity will influence power outages as well as the business climate. Not controlling for variables like economic growth will yield biased estimates of the effect of power outages on firm behavior. In addition, it is also possible that electricity intensive and non-intensive industries face different business climates. In my analysis, I control for omitted variables like economic growth and potential differences in the business climate at the fine geographic level of district. I match outage data to plants at the district-level and exploit variation at the district, time, and industry level to estimate the effect of power outages on electricity-intensive rice and steel mills relative to electricity non-intensive brick kilns.

This paper is related to literature that assesses the impact of electricity availability and pricing on household choices, industrial productivity, and industrial composition.[8] More specifically, this paper adds to the growing literature that analyses how firms respond to electricity scarcity. Firms are found to invest in self-generation capacity at the expense of more productive capital (Reinikka and Svensson, 2002) and out-source part of the production process (Fisher-Vanden et al., 2012). Alby et al. (2013) find that the average firm size of electricity-intensive sectors increases in response to power outages. These studies either use self-reported measures of power outages and/or do not fully account for the correlation between economic growth and power outages. I improve on these studies by mitigating both these sources of bias.

This paper makes three principal contributions to the literature. First, it explores whether there is heterogeneity in firms' responses to power shortages. Literature in this area assumes that the impact of power outages is homogenous on all electricity-dependent firms. I provide evidence that, even within electricity-dependent industries, there are important differences in the impact of electricity shortages. In particular, I show that the adaptation to power outages varies significantly across industries. Second, to my knowledge this is the first study that disentangles the effect of power outages from that of economic growth within a country. Alby et al. (2013) controls for this correlation across countries. Controlling for economic growth at a fine geographic level is important since states/provinces within developing countries have been shown to grow unevenly (Chauduri and Ravallion, 2006). Third, I construct a novel measure of power outages using satellite data. This measure is not subject to reporting bias and can be used to study the impact of power outages in other countries.

I test the predictions of my model, regarding the material usage, capital holdings, generator ownership, output, and profits of rice and steel mills, using plant-level data from the Annual Survey of Industries, India. My results indicate that firms adjust on several margins in response to a change in power outages. With increased power outages, both rice and steel mills become smaller in size and use less electricity. A 10% increase in the mean level of power outages results in steel mills and rice mills using 9.95% and 4.85% less electricity from the public grid, respectively. They also become smaller in size: the same increase in power outages results in a reduction in the value of capital holdings of 9.44% for steel mills and

[8]Recent papers include Abeberese (2013), Khandker et al. (2012), and Rud (2012).

6.17% for rice mills. Variations in the intensity of power outages do not influence generator ownership of rice mills or steel mills. This is indicative of the high costs of installing generators of the scale necessary to power a rice or steel mill.

Overall, rice mills are better able to adjust to power outages than steel mills. First, as power outages increase, rice mills switch to a production technology that is more energy-efficient but less efficient in the use of paddy, the main variable input. This switch results in an increase in material usage and output. In response to a 10% increase in outages, they use 7.71% more paddy and produce 3.16% more rice. Second, as a seasonal enterprise, rice mills make up for a third of the time lost due to outages by operating for more days of the year. In contrast, steel mills produce 11.16% less output when power outages increase and make lower profits. At the mean, a 10% increase in power outages lowers the profits of steel mills by 8.5%.

The results of this paper have important policy implications. In this paper I show that some electricity-intensive industries can alter their production strategies to cope with electricity shortages. Therefore, improvements in electricity infrastructure may only have a modest effect on industrial output. More importantly, improvements in electricity infrastructure will have heterogeneous impact on the manufacturing sector. Some industries will be better able to adapt to power outages. Therefore, industrial sectors in which adaptation to power outages is not possible (for technological reasons) should be given priority electricity and/or discounted generators. Furthermore, since improving the quality of electricity supply for the whole country is likely a costly endeavour, agglomeration non-adaptive electricity-intensive industries should be encouraged.

The rest of the paper proceeds as follows. In section 2, I provide background information about the electricity sector and the industries that I use in my analysis. Section 3 lays out the theoretical model. I use this model to generate comparative static predictions about the input and output choices, and profits of firms as the frequency of power outages increases. Section 4 describes the data that I use. This section also explains the construction of the power outage measure. Section 5 describes my estimation strategy. I present my results in section 6, check for the robustness of my results in section 7, and conclude in section 8.

2. Background

In this section, I provide background details about the electricity sector in India and the three industries (brick kilns, rice mills, and steel mills) that I will use for my analysis. For the electricity sector, I focus on explaining the root causes of unreliability in supply. For the industries, I provide details about the production processes and different coping mechanisms that rice and steel mills can use to deal with power outages. These coping mechanisms will guide the setup of the model in section 3.

2.1. Electricity Sector in India

In July 2012, India experienced the largest blackout in history, leaving approximately 9% of the world's population without power. This infrastructure collapse is sadly indicative of the energy challenges that the country faces. Two important reasons driving the unreliability of electricity supply in India are the lack of investment in infrastructure and excess demand caused by price distortion across consumer categories.

Like most developing countries, India spends too little on infrastructure. For example, South Asia needs to spend around 11% of its GDP on infrastructure to enable prolonged economic growth (World Economic Forum, 2012). But between 2007-2012 India has only spent 5.7% to 8.3% of its GDP on infrastructure[9].

In addition, distortionary pricing of electricity has created incentives for electricity overuse by certain consumer categories. In India, electricity tariffs are determined at the state-level. These tariffs vary substantially across Indian states and across consumer categories within a state. Each Indian State levies a differing tariff on agricultural, commercial, domestic, and industrial consumers. Industrial consumers heavily cross-subsidize the electricity price for the other sectors; in 2000, the industrial tariff was 15 times higher than the agricultural tariff. Over time this tariff differential has gone down, but the gap is still substantial. In 2011, industrial users paid 4 times the price paid by agricultural users (Abeberese, 2013). Since the agricultural sector pays a very low price, the State Electricity Boards (SEBs) have consistently lost money. These losses have left no margin for investment in infrastructure and capacity.

As a result, Indian states have been unable to meet the growing electricity needs of the consumers and use demand side management instead to make up for the deficit. From 1997 to 2009, the SEBs were unable to meet between 11.2% and 16.6% of peak demand (table 3). As a result, power outages are frequent in India. On average, firms in South Asia report experiencing one outage per day. Indian firms report the length of a typical outage to be 3.1 hours and report that outages result in losses equivalent to 6.4% of annual sales.[10] These

[9] These statistics come from a report issued in 2012 by the Federal Chamber of Commerce, India.

[10] Source: Enterprise Survey (World Bank).

self-reported measures indicate that unreliable supply of electricity is a major bottleneck for Indian firms.

Unmet demand for electricity varies significantly across the different regions of India (table 1). While data on electricity deficit at the district-level is difficult to acquire, regional variation in percentage electricity deficit suggests that there is potentially significant cross-district variation in the availability of reliable electricity. I use satellite images to measure power outages at the district-year level to estimate the effect of power outages.

2.2. The Bricks, Rice, and Steel Industries in India

In my empirical analysis I focus on three key industries in India - brick kilns, rice mills, and steel mills.

Brick making is a leading non-electricity-intensive industry in India. It is mainly a seasonal industry that operates in the dry season and its primary material inputs are clay and sand. Clay is mixed with water and made into bricks. The bricks are then fired till they dry and harden. Once cooled, the bricks are ready for sale. Brick-making uses coal or wood as the energy input in its production process. However, brick kilns do use some electricity for two purposes: first, for pumping water (which is then stored in ponds or barrels) and second for illumination of housing of migrant workers. Since water is a storable good, power outages do not affect the production of bricks (unless a power outage lasts for several days). Since bricks are by far the most commonly used building material in India, brick-making is sensitive to economic growth. Therefore, it is an ideal industry for capturing the impact of economic growth on firm choices.

Rice milling is the biggest grain processing industry in India in terms of output. In 2006, India produced 93.35 million metric tons of processed rice as compared to only 69.35 million metric tons of wheat.[11] Between 2003 and 2005, milled rice was the single biggest agricultural export item. Export of rice alone accounted for 16% of the total value of exports. It is a seasonal industry that operates post harvest. The primary input in the rice milling process is paddy (unprocessed rice) and the production process is largely homogenous. In rice milling, paddy undergoes three basic processes: dehusking, polishing, and grading. In the dehusking and polishing processes paddy is rubbed between two surfaces to remove the outer skin. In grading, broken rice is separated from the main batch. The final product is

[11]These statistics are from www.indiastat.com. They were released by the Ministry of Agriculture, Government of India.

ready-to-cook rice. All three processes involved in rice milling are highly electricity-intensive.

Rice mills tend to cope with power outages in two ways. First, they can install generators that generate electricity using diesel during power outages. Second, they can accelerate the production process and produce more output during the time that electricity is available. In particular, dehusking and polishing machines can be run at several different speeds, so rice mills can accelerate the dehusking and polishing process. However, this accelerated production comes at the cost of a higher fraction of broken rice grains which cannot be included in the final rice output. Since paddy is expensive, rice millers prefer to operate the two machines at a low speed for a longer duration of time. This minimizes the breakage of paddy. However, if pressed for time, the mills can process rice as much as three times faster by running the machinery at the highest speed. I incorporate this in my model (section 3) by allowing the mills to choose freely between two different production technologies: milling at a low and high speed. Shifts between the low and high speeds can be made costlessly by simply pressing a button.

Steel milling is also an important industry in India. In 2010, India produced 68.32 million tons of crude steel and was ranked 4th largest steel producer in the world. Steel-making is a fast growing, year-round industry. Unlike rice milling, there are several different methods by which steel can be produced. These production methods can be broadly classified into three categories: Basic Oxygen Furnace (BOF), Electric Arc Furnace (EAF), and Electric Induction Furnace (EIF). Both EAF and EIF methods fall under the minimill production model and are highly electricity-intensive with electricity consumptions of approximately 600 kilowatt hours/ton and 500 kilowatt hours/ton, respectively. These two methods alone account for approximately 60% of steel produced in India. This makes electricity a vital input in Indian steel production. Due to the high energy needs of this industry, unreliability in the supply of electricity can pose serious problems.[12]

In terms of electricity use, the key difference between EAF and EIF is the intensity of electricity usage. An EAF needs huge bursts of electric current in short spurts. The average processing time for a batch of steel using this method is 45 minutes. If the electricity grid is not robust, then such intensive use can blow up the grid. To avoid this possibility, some firms adopt the EIF method. This method requires less electric current for longer. The average processing time under this method is approximately two hours. Overall, the EAF method produces better quality steel than the EIF method. The decision about which type of production technology to install is a one time decision and depends on the firm's business

[12] A full description of the steel making process is beyond the scope of this paper. However, details can be found in Ministry of Steel (2011).

model.[13]

Steel mills tend to cope with power outages in two ways. First, they can install generators.[14] While it is not economically feasible for most plants to shift production from publicly supplied electricity to power generated in-house, firms tend to use generators to safely shut-off the plant in response to power outages. Second, the firms adjust their production hours. Steel mill owners can get the outage schedule from State Electricity Boards and plan their production schedule around it. For example, if power outages are very frequent during weekdays, then some steel mills will choose to operate for 24 hours per day over the weekend to make up for some of the lost time. Unlike rice mills, I do not find any evidence that steel mills can adjust the production mix to cope with outages.

3. Model

I use my model to generate comparative static predictions about the input choices, output, and profits of rice and steel mills as the frequency of power outages increases. My model generates different comparative static predictions for the two industries because they use different adaptation mechanisms to cope with power outages. Since brick kilns do not use electricity in the production process, power outages will not influence their behavior.

3.1. Setup

I assume that firms are risk neutral agents and model their problem as that of static profit maximization. I assume that there is uncertainty about the availability of publicly supplied electricity. Firms believe there will be a power outage with probability $\theta \in [0, 1]$, and this probability is treated as given by the firms. Both rice and steel mills produce output (y) by using capital (k), material (m), and electricity (e) in the production process.[15] If a firm is electricity-constrained, then the maximum quantity of electricity that it can use is $\overline{e}(\theta)$. As θ increases the firm becomes more constrained in its electricity usage ($\frac{d\overline{e}(\theta)}{d\theta} < 0$). All the inputs are complementary ($\frac{\partial^2 f}{\partial x_i \partial x_j} > 0$ for $i \neq j \in \{m, e, k\}$). In my model, economic

[13]Information about the differences between EAF and EIF methods and the mechanisms firms use to cope with power outages comes from interviews with steel mill owners.

[14]In case of vertically integrated mills (mills that produce the iron used in making steel), excess steam energy from iron production is usually used to generate electricity for steel production. Only a few plants are vertically integrated.

For notational simplicity, I do not superscript inputs, outputs or prices by type of firm.

growth can affect the input and output choices of firms by influencing the prices. Further, I assume that the primitives of the model are such that the firm always finds it profitable to operate.

Mills have two ways of coping with power outages. Both rice and steel mills can choose to insure against power outages by investing in self-generation capacity. There is a fixed cost (ϕ) of installing a generator (g).[16] The price of self-generated electricity (p_e^H) is higher than that of electricity consumed from the public network (p_e^L). In addition, rice mills can also adapt by costlessly switching to a technology that uses electricity more efficiently. As discussed in section 2.2, efficiency of the electricity is increased by operating the machinery at a much faster speed. This implies that the efficiency of capital also increases. However, this alternative technology is much less efficient in material usage (paddy wastage increases).

While both rice and steel mills can use technology 1 ($y^1 = f(m, e, k)$), rice mills can also switch to technology 2 ($y^2 = f(a_L m, a_H e, a_H k)$ where $a_H > 1$ and $a_L < 1$). Based on production knowledge gained during field visits to rice mills, I assume that compared to technology 1, technology 2 uses electricity and capital more efficiently ($\frac{\partial y^1}{\partial x} > \frac{\partial y^2}{\partial x}$ for $x \in \{e, k\}$). However, this comes at the expense of using materials less efficiently ($\frac{\partial y^1}{\partial m} < \frac{\partial y^1}{\partial m}$). Rice mills always use technology 2 if along with being more electricity-efficient it is also less costly to use. If this is true then the model will generate identical comparative static predictions for both rice and steel mills. In what follows I explore the only interesting case of my model (this case is also the one described by rice mill owners during field interviews): rice mills have the option to switch to an electricity-efficient yet costly technology. I assume that the marginal cost of producing output is higher under technology 2 than technology 1 ($\frac{dC^1(y)}{dy} < \frac{dC^2(y)}{dy}$) with or without generator ownership. The data show that on average, rice mills' expenditure on paddy is 24 times that of electricity. Therefore, it is highly likely that the increased wastage of material inputs under technology 2 make it the more costly technological choice for rice mills.

Further, I assume that firms know the value of θ and prices. Based on this, both rice and steel mills make the decision about whether or not to install a generator, how much capital to own, and how much materials and energy to use. Rice mills also decide between technology 1 and 2.

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[16] g is 0 if the firm does not own a generator and 1 if it does.

3.2. Equilibrium

In this section I characterize the behavior of rice and steel mills as the frequency of power outages increases.

3.2.1. With Generator

Conditional on generator ownership, the problem faced by rice and steel mills is identical. Both of them use technology 1: steel mills can only use technology 1 and rice mills choose technology 1 because it is less costly. If a firm owns a generator, then it is not constrained in its electricity usage. However, the price of electricity ($p_e = \theta p_e^H + (1-\theta)p_e^L$) increases as power outages become more frequent. The comparative statics for input use are given by:

$$\frac{de_G^*}{d\theta} = (p_e^H - p_e^L)\left(\frac{f_{kk}f_{mm} - f_{mk}f_{mk}}{\mid f \mid}\right) < 0$$
$$\frac{dm_G^*}{d\theta} = (p_e^H - p_e^L)\left(\frac{f_{mk}f_{ek} - f_{ek}f_{mm}}{\mid f \mid}\right) < 0$$
$$\frac{dk_G^*}{d\theta} = (p_e^H - p_e^L)\left(\frac{f_{ek}f_{km} - f_{mk}f_{kk}}{\mid f \mid}\right) < 0$$

$\mid f \mid$ is the determinant of the third principle minor of the Hessian matrix of the production function. By concavity of the production function, $\mid f \mid < 0$. Further, concavity of the production function and complementarity between all the inputs imply that $\frac{de_G^*}{d\theta} < 0$, $\frac{dm_G^*}{d\theta} < 0$, and $\frac{dk_G^*}{d\theta} < 0$. As power outages become more frequent, generator owning firms use less of all the inputs. As a result, they produce less output and are less profitable.

3.2.2. Without Generator

The maximization problem for rice and steel mills differs because rice mills have the option of switching to technology 2 while steel mills do not.

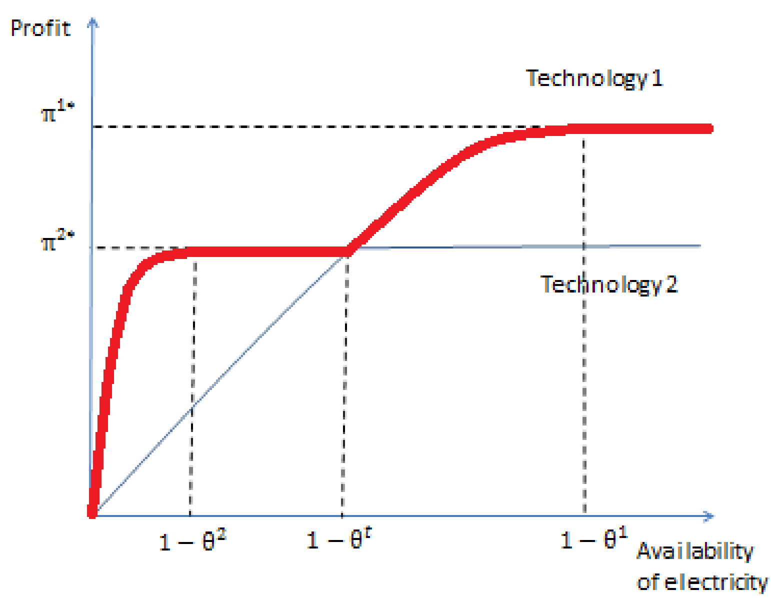
Steel Mills: If a steel mill does not own a generator and the electricity constraint is binding, then its electricity usage is determined by $e = \bar{e}(\theta)$. As power outages increase, the the electricity usage decreases ($\frac{d\bar{e}(\theta)}{d\theta} < 0$). In this case the comparative statics for material and capital usage are given by:

$$\frac{dm^*_{NG}}{d\theta} = \left(\frac{-f_{m\bar{e}}f_{kk} + f_{mk}f_{\bar{e}k}}{f_{mm}f_{kk} - f_{mk}f_{mk}}\right)\frac{d\bar{e}(\theta)}{d\theta} < 0$$
$$\frac{dk^*_{NG}}{d\theta} = \left(\frac{-f_{k\bar{e}}f_{mm} + f_{mk}f_{\bar{e}m}}{f_{mm}f_{kk} - f_{mk}f_{mk}}\right)\frac{d\bar{e}(\theta)}{d\theta} < 0$$

Concavity of the production function and complementarity between all the inputs imply that $\frac{dm^*_{NG}}{d\theta} < 0$ and $\frac{dk^*_{NG}}{d\theta} < 0$. As power outages become more frequent, steel mills that do not own generators use less of all the inputs. As a result, they produce less output and are less profitable.

Rice Mills: In this section, I trace the input usage, output, and profits of non-generator owning rice mills as power outages increase. I focus on the intuition for the predictions. The detailed proofs are provided in appendix 1.1. Rice mills choose between technology 1 and 2. Figure 1 traces out the profit function for a mill.

Fig. 1.— Profits and Outages



As power outages increase, the firm switches from using technology 1 to technology 2. If the firm is unconstrained in its electricity usage, then it prefers using technology 1 ($\pi^{1*} > \pi^{2*}$) because the marginal cost of production is higher for technology 2. On the other hand, if the firm's electricity constraint binds very strongly, then the firm prefers to use technology 2. If the electricity usage of a firm is highly constrained, then by switching to the more electricity-efficient technology (technology 2) it can produce more output with the same amount of electricity. If the increase in output is enough to compensate for the higher marginal cost of production under technology 2, then the firm prefers using technology 2.

Starting from no power outages ($\theta = 0$), as power outages increase the firm's choices change in the following manner:[17]

- As long as $\theta < \theta^1$, the firm will choose technology 1 and is not electricity-constrained. An increase in outages has no effect on its choices because the firm is unconstrained in electricity usage.
- For $\theta^1 < \theta < \theta^t$, as outages increase, the firm continues to use technology 1. The use of all three inputs, output, and profits falls (these predictions and the reasoning behind them are identical to the predictions and reasoning for non-generator owning steel mills).
- As outages increase beyond $\theta = \theta^t$, the firm switches from technology 1 to 2.
  - *Profit remains unchanged:* Since the firm switches between the two technologies at the point of indifference, its profit remains unchanged.
  - *Output increases:* The firm switches to a more costly technology but its profit remains unchanged. Therefore, it must be that the firm's output increases to make up for the higher cost of using technology 2.
  - *Material usage increases:* Since, the firm is switching to a more electricity efficient technology, complementarity between electricity and material implies that material usage will increase.
  - *Capital:* The prediction about capital holdings is ambiguous. When the firm switches to technology 2, capital also becomes more productive. The firm's capital holdings decrease if the firm is experiences diminishing returns to capital when it switches between the two technologies. In my model this is equivalent to the marginal product of capital being highly elastic with respect to capital. Otherwise, capital holdings will increase.

[17] And moving from right to left along the x-axis in figure 1.

- For $\theta^t < \theta < \theta^2$, the firm will choose technology 2. Conditional on its technology choice, the firm is not electricity-constrained. An increase in outages has no effect on choices.
- For $\theta > \theta^2$, the firm continues to use technology 2. As power outages increase, the use of all three inputs, output, and profits falls (these predictions and the reasoning behind them are identical to the predictions and reasoning for non-generator owning steel mills).

Generator Ownership: Based on the two sets of demand functions, the mill will decide to install a generator if:

$$\begin{aligned} & p_y f(m_G^*, e_G^*, k_G^*) - p_m m_G^* - (\theta p_e^H + (1-\theta) p_e^L) e_G^* - p_k k_G^* - \phi \\ \geq \; & f(m_{NG}^*(\theta), \bar{e}(\theta), k_{NG}^*(\theta)) - p_m m_{NG}^*(\theta) - p_e \bar{e}(\theta) - p_k k_{NG}^*(\theta) \end{aligned}$$

The effect of power outages on generator installation depends on the intensity of power outages and the cost of installation. If there are no power outages ($\theta = 0$), then it is never optimal for the firm to invest in self-generation capacity. Similarly, if there is no publicly available electricity ($\theta = 1$), then the firm will always install a generator. Therefore, $\exists \widehat{\theta}$ such that $\forall \theta > \widehat{\theta}$ firm will install a generator. As the cost of generator installation (ϕ) increases the threshold ($\widehat{\theta}$) above which the firm installs a generator will increase.

3.3. Testable Predictions of the Model

To summarize, my model generates different testable predictions for rice and steel mills because ye two industries use different adaptation mechanisms to cope with power outages. A novel feature of my model is that in-line with my industrial knowledge, I assume that the production function can be costlessly changed by rice mills to use electricity more efficiently. Furthermore, I make no assumptions about the production function besides complementarity and concavity to generate my predictions.

For steel mills, as power outages increase, the use of all inputs, output, and profits fall. For rice mills the predictions are more nuanced. If a rice mill does not own a generator and the change in power outages is such that the firm switches from technology 1 to 2, then profit remains unchanged, material usage, and output increases. Under the conditions discussed in the previous section, capital usage also falls. Otherwise, material usage, output, and profits fall.

4. Data Sources and Summary Statistics

4.1. Plant Data

The plant-level data that I use comes from India's Annual Survey of Industries. The ASI is an annual survey of approximately $30,000$ registered factories in India. The sampling frame consists of all firms that either employ at least 10 workers while using electricity or at least 20 workers without using electricity. I use the 5-digit NIC code to identify rice mills and brick-making firms and the 4-digit NIC code to identify steel-making firms. For my analysis, I use ASI for the years 1999 - 2000, 2001 - 2002, 2004 - 2005, and 2009 - 2010.

In each wave, firms report the quantity of electricity purchased, average price paid per kilowatt-hour, and total purchase value in rupees. Firms also report the quantity of electricity generated by the firm itself for consumption. This information is used to construct a dummy for whether the firm owns a generator or not. Firms also report the quantity, price, and total purchase value of material inputs and outputs. For the value of capital, I use the book value of plant and machinery at the start of the reference period. District names for the first two waves are obtained by creating a cross walk with the National Sample Survey (NSS), India. The analysis is restricted to districts in which I observe at least one rice or steel mill and one brick kiln. Using this criterion, I retain 60% of firms and 40% of districts from the original sample.

4.2. Construction of the Measure of Power Outage

To construct the measure of power outage I use satellite data from the United States Air Force Defense Meteorological Satellite Program (DMSP-OLS Nighttime Lights Global Composites). This data is collected by the US Air Force Weather Agency. Under this program, the satellite has been orbiting the Earth 14 times each day since the 1970's. The digital archive is available for all years between 1992 and 2010.[18] Nightlights emanating from each location on Earth are observed by the satellite between 8:30 p.m. and 10:00 p.m. local time.

The National Geophysical Data Center (NGDC) processes and aggregates these raw data to create the average visible lights (AVL) composite. NGDC uses this composite to derive two other cloud free composites of nighttime lights: the stable lights (SL) and the normalized visible lights (NVL) composite . I use these two composites to quantify the with-

[18]This data can be downloaded from: http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

in year variation in light intensity at a point and use this variation as a measure of power outages at that point. The details of how I measure outages is discussed in the next section.

The data cleaning process adopted results in composites that mostly capture man-made light. The images thus created attach a particular value of light intensity to every 30 arc second output pixel (approximately 0.86 square kilometers at the equator). The AVL composite contains the average of the visible band digital number values with no further filtering. The intensity of each pixel ranges from 0-63.

I construct the measure of power outages at the district-level. Nightlight data has been used to study economic growth, poverty, and spatial apportionment of population,[19] but to my knowledge, this is the first use of nightlights data in economics to study power outages. As previously discussed I use two composites, the stable lights (SL) composite and the normalized average visible lights (NAVL) composite, to construct my measure of power outage. Both the composites are derived from the AVL composite.

The stable lights (SL) composite restricts the AVL to sites with persistent lighting like cities and towns.[20] Data values range from 1-63. The normalized average visible lights (NAVL) composite is produced by multiplying intensity recorded in the AVL composite by the percent frequency of light detection.[21] For example, if a light is only observed half the time, then it will be discounted by 50%. Both these composites correct for natural sunlight and cloud cover. Figures 4 and 5 present the SL and NAVL composites for India in 2004, respectively. As expected, the NAVL composite will be less bright than the SL composite. I use this difference in brightness to measure power outages.

For each location, the wedge between the SL composite and the NAVL composite is going to be larger if observed lighting is more variable. An area with more frequent power outage is going to have a higher variability in observed lighting. Thus, the ratio of the two composites is a measure of power outage intensity.

As discussed in section 2, power outages are used as a method of demand management. Therefore, it is reasonable to assume that at any given location, power outages are highly

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[19]Literature in this area includes (but is not limited to) the following: economic growth (Chen and Nordhous *2011), Henderson et al. (2012), and Kulkarni et al. (2011)), poverty (Elvidge et. al, 2009), and spatial apportionment of population (Elvidge et. al, 1997).

[20]Background noise (including fires and ephemeral lights) is identified and replaced with values of zero.

[21]The inclusion of the percent frequency of detection term normalizes the resulting digital values for variations in the persistence of lighting. This product contains detections from fires and a variable amount of background noise.

correlated across day and night. That is, more frequent power outages at night imply more frequent power outage during daytime (when most of the manufacturing industries are operating). My empirical strategy relies on variation in outages across district and time. Since day and night time outages are highly correlated in India, my measure of outages is a good proxy for day time outages.

Next, I describe the construction of the power outage measure. For each year (τ), I exclude top-coded observations as the pixel reading at these points is saturated. Saturation makes discerning power outages impossible for these points. I also exclude observations that emit no stable light; these are likely to be forests and land with no permanent human settlements. From the set (V_{j_τ}) of remaining observations within each district (j) at time (τ), I construct the ratio of the two composites at each 30 arc second grid point (i). I take the median of the power outage at all the points (i) within each district (j) and treat it as the power outage measure for that district in that year. Since the accumulation of capital holdings is a dynamic process, it is going to depend on current as well as past power outages. Thus, for each year (t) in which I observe the firms, I take the average of the yearly power outage measure over the last three years[22] and treat this average as the measure of power outages that these firms face:

$$O_{jt} = \sum_{\tau=t-2}^{t} \left(\underset{i \in V_{j\tau}}{median} \left(\frac{SL_{ij\tau}}{NAVL_{ij\tau}} \right) \right)$$

This measure does not directly capture differences in growth of the local economy as the observed lighting in an economically more developed location is going to be proportionately higher in both the composites. However, as discussed previously, it might be the case that areas that are more developed have a higher incidence of power outages due to higher demand. These concerns are addressed in the empirical strategy.

4.3. Summary Statistics

My estimation strategy requires that I observe rice/steel mills and brick kilns within the same district. This restriction leaves me with 60.1% of the original sample. Table 2 presents summary statistics for the restricted sample. In comparison to brick kilns, rice/steel mills tend to be larger in size, use more electricity, and are more likely to own a generator. The

[22] The ASI waves that I use are approximately three years apart. I average the outage measure over three years to avoid overlap.

value of capital is missing for approximately 10% of the sample. Input and output data for the 2004 wave has been imputed in some instances. Therefore, I exclude this wave from the analysis when looking at input and output data. For the remaining three waves, input and output data is missing for approximately 13% of the sample.

The power outage measure takes values between 1 and 3.5. A value of one means that there are no discernible power outages at the median location in the district. Similarly, a value of two means that there are power outages half the time at the median location in the district. The mean for the power outage measure is 1.72. This implies that the average district in my sample has electricity for only 14 hours a day. At the mean, a 10% increase in my measure of power outage translates into an increase of one hour in power outages.

5. Estimation Strategy

The key empirical challenge in testing the predictions of my model is controlling for variables that move in tandem with power outages and also influence the decisions made by firms. I flexibly control for such confounding variables in my empirical strategy.

5.1. Main Specifications

I use two empirical specifications to test the predictions of my model. Both specifications estimate the differential effect of power outages on electricity-intensive rice and steel mills relative to electricity non-intensive brick kilns. The two specifications address two important endogeneity concerns which I discuss during the presentation of each specification.

5.1.1. Specification 1

The first endogeneity concern is that power outages may be correlated with variables that influence the overall business climate faced by firms in a particular geographic location. Examples of such variables include economic growth and local state capacity. Such omitted variables will affect both power outages and the choices made by firms (by affecting the business environment in which firms operate).

In the first specification, I address this concern by including district-year fixed-effects. This allows me to flexibly control for omitted variables that influence both power outages and firm choices within a district in a given year. I use within district heterogeneity in firm type to identify the effect of power outages on electricity-intensive firms (rice and steel mills) relative to electricity non-intensive firms (brick kilns). Since power outages do not directly impact the choices of brick kiln, I am able to estimate the effect of power outages on the choices of rice and steel mills relative to brick kilns.[23]

Let y_{ijkt} be the outcome of interest for firm i, in district j, in industry k, and in year t. I estimate the following specification:

$$y_{ijk't} = \alpha_k^y O_{jt} + \gamma_1 \upsilon_k + \gamma_2 \upsilon_{jt} + \gamma_3 X_{jkt} + \varepsilon_{ijkt}$$

Here the omitted industry is brick kilns; $k \in \{$rice mills, steel mills$\}$;$k' \in \{$rice mills, steel mills, brick kilns$\}$. O_{jt} is the power outage measure in district j at time t. For comparability across the three industries, I estimate this specification in terms of percentage changes in the outcome variable. The coefficients of interest are α_k^y: each coefficient estimates the effect of power outages on outcome variable y for industry k relative to its effect on the same outcome variable for brick kilns.

υ_k denotes fixed-effects by industry, υ_{jt} denotes district-year fixed-effects, and X_{jkt} includes rainfall shocks. υ_k captures the level effect of being industry k relative to brick kilns. υ_{jt} captures all the omitted variables that are correlated with outages and influence all three industries in the same way. X_{jkt} allows district-level rainfall shocks to differentially influence each of the three industries. Rainfall may influence the input market for rice (by increasing the yield of paddy) and maybe correlated for power outages. I control for this possibility at the district-year level by including X_{jkt} in my specification. X_{jkt} is the interaction of rainfall shocks in district j in year t with the dummy for each industry.

In general, time varying variables that are correlated with outages and impact the three industries differently may bias my results. Such variables will operate via two channels. First, they may differently altering the demand for output. For example, economic growth (which is correlated with power outages) may induce consumers to demand more steel than bricks. Second, they may differently influence the input markets that these industries face. For example, rainfall affects the input market for rice but not bricks and steel and may be correlated with power outages.

In my model all demand side shocks will operate via prices. To rule out the possibility that differences in demand side shocks are driving my results, I will show that outages are not differentially correlated with the relative prices faced by the three industries.

[23] District-year fixed-effects completely absorb the correlation between power outages and economic growth. Since power outages do not directly influence the production process of brick kilns, it is reasonable to assume that the coefficient estimated for brick kilns should be zero.

Furthermore, as discussed above, a key variable that can differentially influence the input markets is rainfall. Rainfall will influence outages in two ways. First, electricity networks in developing countries are usually not robust to rainfall and storms. Thus, rainfall will directly result in outages. Second, positive shocks to monsoon rainfall have been shown to increase agricultural yield thereby increasing district-level wealth. The increase in wealth will increase the demand for electricity. As a result, rainfall will cause more outages due to supply side constraints. Table 5 shows that both monsoon and yearly rainfall increase the frequency of power outages. In addition to influencing power outages, rainfall will also influence the input market for rice mills. Monsoon rainfall shocks obviously affect the yield of paddy, and therefore, have a direct impact on rice mills. both my specifications address this concern by allowing district-level rainfall shocks to differentially influence each industry.

5.1.2. Specification 2

The second endogeneity concern is that the three industries may face different business environments within a district. For example, a district government may care more about electricity intensive industries than electricity non-intensive industries. If this is true then the government will help electricity-intensive industries by providing more reliable electricity supply in the district and by giving them flexible loans, tax rebates, and special concessions.

In the second specification, I address this concern by including district-industry fixed-effects. This allows me to flexibly control for differences in the business environment faced by the three industries at the district-level.

I estimate the following specification:

$$y_{ijk't} = \alpha^y O_{jt} + \alpha^y_k O_{jt} + \gamma_1 \upsilon_{jk} + \gamma_2 \upsilon_t + \gamma_3 X_{jkt} + \varepsilon_{ijkt}$$

$y_{ijk't}$, O_{jt}, X_{jkt}, k, and $k^{'}$ are defined the same way as in specification 1. υ_{jk} denotes district-industry fixed-effects and υ_t denotes year fixed-effects. Here I control for the correlation between power outages and economic growth less flexibly. Since brick kilns do not use electricity in their production process, they act as the control for economic growth. α^y estimates the effect of power outages on brick kilns. As in specification 1, the coefficients of interest are α^y_k : each coefficient estimates the effect of power outages on outcome variable y for industry k relative to its effect on the same outcome variable for brick kilns.

Compared to specification 1, specification 2 controls for the correlation between power outages and economic growth less flexibly. However, since specification 2 controls for both sources of endogeneity it is more robust compared to specification 1.

For both specifications the outcome variables are electricity bought from the public grid (e^p), total electricity usage (e^t), value of capital (k), material (m), output (y), and a dummy for generator ownership (g). I also look at whether firms respond to power outages in two additional ways that are outside my model. I assess whether adjust at the extensive or intensive margin of operation; that is, a dummy for whether the firm operates or not (short-run shutdown), and the length of operation.

I estimate both specifications using Poisson Pseudo-Maximum Likelihood (PPML). PPML estimates the coefficients in terms of percentage changes and is able to handle zeros. This makes PPML a very suitable method for my data.[24] Furthermore, PPML yields consistent point estimates for a broad class of models; specifically, the dependent variable does not have to follow a Poisson distribution or be integer-valued. The standard errors are estimated using Eicker-White robust covariance matrix estimator. This fully accounts for heteroskedasticity in the model.[25] The use of PPML for continuous variables was first proposed by Gourieroux et al. (1984). Silva and Tenreyro (2006, 2011) run simulations to compare PPML with log-linear models. They find that unlike the log-linear model, the PPML estimator yields unbiased estimates in the presence of heteroskedasticity and can handle zeros in the dependent variable. As a robustness check, I also estimate and report the results for the log-linear estimation.

5.1.3. Profits:

Since profits can be negative, I cannot estimate a Poisson or a log-linear model. Therefore, I estimate linear regression models instead.

The linear estimation equation comparable to specification 1 is:

$$\pi_{ijkt} = \alpha_k^y O_{jt} + \gamma_1 \upsilon_k + \gamma_2 \upsilon_j + \gamma_3 \upsilon_t + \gamma_4 X_{jkt} + \varepsilon_{ijkt}$$

In this specification υ_j denotes district fixed-effects and there is no excluded industry.

The linear estimation equation comparable to specification 2 is:

[24] Electricity usage data for brick kilns takes on the value of zero as brick making does not use electricity in the manufacturing process. This makes the use of a log-linear model impossible for electricity usage.

[25] This method of estimation for the covariance matrix does not rely on the restrictive Poisson assumption of the equality of the mean of dependent variable and its variance.

$$\pi_{ijkt} = \alpha_k^y O_{jt} + \gamma_1 \upsilon_{jk} + \gamma_2 \upsilon_t + \gamma_3 X_{jkt} + \varepsilon_{ijkt}$$

The coefficients of interest are α_k^y : each coefficient captures the effect of power outages on industry k.

5.2. Alternative Specification

I also estimate an alternative specification that allows me to explore the direction of biases that result if omitted variables like economic growth are not properly controlled for. Here district fixed-effects control for differences in the average level of power outages and economic growth in a district. Additionally, I control for shocks to the local economy by controlling for rainfall shocks in the monsoon months. I estimate the following specification:

$$y_{ijk't} = \alpha^y O_{jt} + \alpha_k^y O_{jt} + \gamma_1 \upsilon_k + \gamma_2 \upsilon_j + \gamma_3 \upsilon_t + \gamma_4 X_{jkt} + \varepsilon_{ijkt}$$

All the outcome variables are the same as before. Here α^y captures the effect of power outages on brick kilns. This is the effect of power outages that is due to its correlation with economic growth, etc. If power outages are positively correlated with economic growth, then α^y will be positive. α_k^y is the effect of power outages on industry k (rice or steel mills) after controlling for the correlation of power outages with economic growth.

6. Results

I first present evidence that my measure of power outages is a good predictor of electricity shortage and then present results for the effect of power outages on choices of firms. When presenting my results, I indicate the expected percentage change in the outcome variable when power outages increase by 10%. At the mean, a 10% increase in the power outage measure corresponds to power outages increasing by one hour everyday. I focus on the results of my main specifications. For each outcome variable results from both specifications 1 and 2 are presented in the same table. Each column indicates the fixed-effects that are included. The results from the alternative specification and robustness checks are discussed at the end.

6.1. Validity of Power Outage Measure

I check for the validity of my measure of power outages using two external data sources: state-level percentage deficit during peak demand periods in India and self-reported night-time outage data from the Rural Economic and Demographic Survey (REDS, 2005-2006) conducted in India. Both datasets provide strong evidence in support of the validity of my power outage measure.

First, my measure of power outage is a strong predictor of state-level percentage deficit of electricity during peak demand periods. I regress percentage of electricity deficit at the state-level on outages. An increase in power outages positively affects peak electricity deficit; the estimated coefficient is significant at 1% (table 3, column 1). Second, I regress my measure of power outages with a question about the regularity of night time electricity from the REDS.[26] An increase in outages is positively associated with irregularity of electricity supply at night time; the estimated coefficient is significant at 1% (table 3, column 2).

Furthermore, night time power outages are correlated with peak time electricity deficit. Table 4 shows that nighttime irregularity in electricity supply from the REDS data is positively associated with peak electricity deficit; the estimated coefficient is significant at 1%. Power outages are likely to be highest during peak demand times because the electricity network is unable to meet the demand. Peak demand occurs both during day and night hours (figure 8 provides evidence to support this claim for the electricity grid of the Northern Region in India). Most businesses and firms operate during the daytime and they will be susceptible to power outages.

6.2. Electricity Usage and Profits

Tables 6 presents the results for the effect of power outages on electricity usage. Increased power outages result in rice and steel mills consuming less publicly provided electricity. In specification 1 (district-year fixed-effects), a 10% increase in the mean level of power outages results in steel mills and rice mills using 9.95% and 4.85% less electricity, respectively. The negative effect of power outages on electricity usage persists when I look at the total electricity usage[27] of the firms.

Similarly, in specification 2 (district-industry fixed-effects) an increase in the frequency

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[26] The wording of the question is: "How regular is your power supply after sunset?"

[27] Total electricity is the sum of electricity bought from the public grid and electricity that is self generated.

of power outages reduces the electricity consumption of steel and rice mills but the coefficients estimated for rice mills are not significant. Since 53% of brick kilns do not use electricity, brick kilns do not perfectly control for the effect of economic growth on electricity usage. Therefore, the effect of power outages on rice and steel mills is biased towards zero in specification 2. This explains why the results for electricity usage of rice mills are not significant. It also explains why the upper bound of the 95% confidence interval for coefficient estimated for steel mills is closer to zero in specification 2 compared to specification 1.

I find that even though power outages negatively affect the electricity usage of both rice and steel mills, their impact on the profits of the two industries is different. In both specifications (1 and 2) an increase in power outages significantly lowers the profits of steel mills but not rice mills. For example, in specification 1, a 10% increase in power outages lowers the profits of steel mills by 8.5% (table 7). This indicates that rice mills are better able to cope with electricity shortage than steel mills.

6.3. Material Usage and Output

My model predicted when rice mills switch between technologies their material consumption and output should increase. My results for material usage and output indicate that rice mills adapt to power outages by switching to a more electricity-efficient technology (tables 8 and 9). I find that the material usage of rice mills goes up in both specifications. In specifications 1 and 2, a 10% increase in power outages results in rice mills using 7.71% and 16.23% more paddy, respectively. I find similar results for output. In specification 2, a 10% increase in the incidence of power outages induces rice mills to produce 3.16% more output. In specification 1, the effect of power outages on output is positive (close to zero) but not significant.

My interviews with steel mill owners/employees indicated that, unlike rice mills, steel mills cannot alter their technology in response to power outages. Since steel mills cannot alter their production technology, my model predicts that their material usage and output will fall as power outages become more frequent. In specifications 1 and 2, a 10% increase in power outages results in a 11.16% and 16.23% decrease in output produced by steel mills, respectively. Power outages also affect the material usage of steel mills negatively, but the coefficient is not significant.

6.4. Generator Ownership and Capital

Table 10 presents results for the effect of power outages on capital holding and generator ownership of rice and steel mills. I find that both rice and steel mills adjust their capital holdings in response to power outages. In specification 1, with a 10% increase in the mean level of power outages, rice and steel mills reduce the value of their capital holdings (relative to brick kilns) by 9.44% and 6.17%, respectively. The coefficient estimates for specification 2 are similar in magnitude to those for specification 1 but are insignificant.

I do not find any evidence that rice and steel mills respond to short-run increases to power outages by investing in self-generation capacity. Rice mills only use self-generated electricity if there is an imminent deadline. Similarly, steel mills only use self-generated electricity to safely shutdown the plant. The electricity consumption of steel mills is high and switching production to self-generated electricity over prolonged time periods is not feasible. So, it is not surprising that rice and steel mills do not respond to short-run changes in power outages by installing self-generation capacity.

6.5. Intensive and Extensive Margin

As power outages increase, firms can adjust on two other margins. First, they can adjust on the extensive margin and choose to shutdown in the short-run. Second, electricity-intensive firms can adjust on the intensive margin; they can choose to operate for longer in order to make up for production time lost due to power outages.

To test for adjustments at the intensive margin, I investigate whether the number of months of operation of rice and steel mills alters with changes in power outages. Steel mills are all-year enterprises while rice mills are seasonal enterprises. Therefore, only rice mills can use this margin of adjustment. In specification 1, I find that a 10% increase in the mean level of power outages results in rice mills operating for 1.77% more months (table 11). This means that rice mills operate for 5 more days every year and are able to makeup for a third of the time the production time lost due to electricity shortage.

On the extensive margin, some firms might choose to shut down if power outages become extremely frequent. Firms that have shut down permanently are not part of the ASI sample. However, the ASI sample does include firms that have temporarily stopped operating. In the short-run I do not find evidence that firms shut down in response to power outages (table 11).

6.6. Alternative Specification

The direction and magnitude of the effects estimated in the alternative specifications are very similar to those estimated in specification 1. The results are presented in tables 13 and 14. As power outages increase, brick kilns become bigger. This indicates that power outages are positively correlated with economic growth. If omitted variables like economic growth are not taken into account, then I would find that the size of rice and steel mills increases when power outages become more frequent. These results indicate that the effects of power outages currently estimated in the literature are likely to be upward biased.

6.7. Omitted Variable Bias

My analysis suggests that economic growth is positively correlated with power outages. It is possible that the income elasticity of the demand for output differs across the three industries. In my model differences in the income elasticity of demand will enter through the prices. A firm's production decision is based on the relative input-output price. In table 12, I check for the co-movement of relative prices and power outages.[28] In both specifications 1 and 2, I find no evidence of prices moving in tandem with power outages. Therefore, my results are not driven by differences in relative prices.

7. Robustness Checks

To check for the robustness of my results I estimate two alternative specifications. Both these specifications include district-year fixed effects.[29] The first specification estimates the effects of power outages using a log-linear form. The log-linear model cannot be estimated for electricity usage because a significant proportion of brick kilns do not use electricity. The results for the remaining input choices and output are presented in table 15. All the estimated coefficients are similar in size, magnitude, and level of significance to the estimated coefficients in the main specification (with one exception). Power outages have an

[28]Relative price is defined as the ratio of the price of output to material inputs. Material inputs are the biggest short run expenditure for both rice and steel mills; for rice and stell mills on average material constitutes 95% and 86% of total short-run expenditure, respectively. So the price of material inputs is the most relevant input price.

[29]I have also run robustness checks with district-industry fixed effects. The results are similar. I have not including them in the paper for berevity but the results are available upon request.

insignificant effect on the capital holdings of steel mills.

In the second specification, I convert the measure of power outages into the fraction of time that electricity is available. Tables 16 and 17 present the results of this specification. Since the dependent variable is availability of electricity (instead of the shortage of electricity), I expect the coefficients to have the opposite sign of all the previous estimates. All the results are similar to those of the main specification.

8. Conclusion

In this paper, I have examined the impact of power outages on the choices made by Indian firms. I have allowed firms to use industry specific adaptation mechanisms and traced the effects of power outages on firm size, output, and profits for rice and steel mills in India. I have also analyzed whether firms can adjust to power outages by altering their production strategy and length of operation.

In the process, I have constructed a novel measure for the frequency of power outages using satellite data. This has allowed me to assess the impact of power outages at a much finer geographic level than previous empirical studies in this area. I have also specifically controlled for variables outside my model that influence both power outages and the economic environment that businesses face.

In my empirical strategy, I have identified the effect of power outages on electricity-intensive industries relative to their effect on electricity non-intensive industries. I have found evidence that even within electricity-intensive industries there are significant differences in the adaptation capacity to power outages. I have found that short-run changes in power outages do not induce firms to install generators. My results show that rice mills adapt to changes in power outages in two important ways. First, rice mills adjust by switching to a production technology that allows them to process more material inputs in the given amount of time (they operate the plant at a much faster speed). I find that the material usage and output of rice mills goes up significantly as power outages become more frequent. Second, they make up for a third of the loss in productive time by operating for more days. Since rice mills have more adaptation mechanisms available to them, an increase in power outages negatively affects the profitability of steel mills but not that of rice mills.

My results have clear policy implications. First, if a significant fraction of electricity-intensive industries can limit the adverse effects of inadequate electricity, then improvements in electricity infrastructure (reliability of electricity) will have a modest effect on industrial output. Second, improvements in electricity infrastructure will have heterogeneous effects on industrial input usage and production due to differences in adaptation capacity. Due to the heterogeneous effects of power outages, industries for which adaptation to power outages is not possible should be given priority electricity. Third, agglomeration of non-adaptive electricity-intensive industries should be encouraged if improving the quality of electricity supply for the whole country is a costly endeavour. Fourth, governments should focus on reducing the frequency of power outages faced by non-adaptive electricity-intensive industries rather than improving other aspects of the business environment. For example, for countries that suffer from power outages, giving tax breaks, subsidies, or infant industry protection to non-adaptive electricity-intensive industries might not increase industrial output and enhance firm growth if power outages remain frequent.

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1. Appendix

1.1. The maximization problem of rice mills:

I characterize the equilibrium choices of non-generator owning rice mills in three steps. First, I show that if a rice mills is not constrained in electricity usage, then it will use technology 1. Second, I characterize the conditions under which the firm will find it profitable to switch from technology 1 to technology 2 as power outages increase. Last, I characterize how the input choices of the firm alter at the point that the firm finds it optimal to switch from technology 1 to technology 2.

Step1: The unconstrained firm uses technology 1.

To show that $\pi^{1*} > \pi^{2*}$button, I will first show that $y^{1*} > y^{2*}$. The optimal input usage of a firm is characterized by $p_y = \frac{dC^i(y)}{dy}$. Since the marginal cost of output is higher for technology 1 than technology 2 ($\frac{dC^1(y)}{dy} < \frac{dC^2(y)}{dy}$), the firm will produce more output if it uses technology 2. Therefore, $y^{1*} > y^{2*}$.

Given that $y^{1*} > y^{2*}$, profits will be higher under technology 1:

$$\begin{aligned}
\pi^{1*} &= \int_{y=0}^{y^{1*}} (p_y - \frac{dC^1(y)}{dy})dy \\
&= \int_{y=0}^{y^{2*}} (p_y - \frac{dC^1(y)}{dy})dy + \int_{y=y^{2*}}^{y^{1*}} (p_y - \frac{dC^1(y)}{dy})dy \\
&> \int_{y=0}^{y^{2*}} (p_y - \frac{dC^2(y)}{dy})dy + \int_{y=y^{2*}}^{y^{1*}} (p_y - \frac{dC^1(y)}{dy})dy \\
&> \int_{y=0}^{y^{2*}} (p_y - \frac{dC^2(y)}{dy})dy \\
&> \pi^{2*}
\end{aligned}$$

Step 2: As outages increase firms will switch from using technology 1 to technology 2

Note that if the firm is unconstrained, then it chooses technology 1. I show that as power outages become very frequent ($\theta \rightarrow 1$) then firms will choose technology 2.

The change in profits as power outages increase is given by:

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$$\begin{aligned}
\lim_{\theta\to 1}\frac{\partial \pi^1}{\partial \theta} &= \lim_{\theta\to 1}(f_e(m^1(\theta),\overline{e}(\theta),k^1(\theta))\frac{\partial \overline{e}}{\partial \theta} - p_e^L\frac{\partial \overline{e}}{\partial \theta}) \\
\lim_{\theta\to 1}\frac{\partial \pi^2}{\partial \theta} &= \lim_{\theta\to 1}(f_e(a_L m^2(\theta),a_H\overline{e}(\theta),a_H k^2(\theta))\frac{\partial \overline{e}}{\partial \theta} - p_e^L\frac{\partial \overline{e}}{\partial \theta})
\end{aligned}$$

Electricity is more productive in technology 2. Therefore,

$$\lim_{\theta\to 1} f_e(a_L m^2, a_H\overline{e}, a_H k^2) > \lim_{\theta\to 1} f_e(a_L m^2, \overline{e}, a_H k^2)$$

If $a_L m^2(\theta) > m^1(\theta)$ and $a_H k^2(\theta) \geq k^1(\theta)$, then at equilibrium, the marginal product of electricity will be higher under technology 2. That is,

$$\lim_{\theta\to 1} f_e(a_L m^2(\theta), a_H\overline{e}(\theta), a_H k^2(\theta)) > \lim_{\theta\to 1} f_e(m^1(\theta), \overline{e}(\theta), k^1(\theta))$$

This implies that the firm will choose technology 2. Therefore, as power outages increase (the firm moves from unconstrained profit maximization to constrained profit maximization), the firm switches from technology 1 to technology 2.[30]

Step 3:

Claim 1 *Assume that θ is such that the firm decides to shift from using technology* 1 *to using technology* 2 *as power outages increase. Then, when the firm switches from technology* 1 *to* 2*:*

1. *Material usage will increase if a_H is sufficiently high*
2. *Capital usage will increase if the marginal product of capital is not responsive to input use.*
3. *Profit will stay the same.*
4. *Output will increase.*

Materials: The optimal level of material usage is governed by:

$$f_m(a_L m^{2*}, a_H e^{2*}, a_H k^{2*}) = f_m(m^1(\theta), \overline{e}(\theta), k^1(\theta)) = p_m$$

[30]Concavity of the production function implies that the profit functions cross only once.

When a firm switches from technology 1 to technology 2, two competing forces are exerted on material usage: a_H increases m^{2*} because $a_H f_{a_H e} > f_e$ ($a_H f_{a_H k} > f_k$) and a_L decreases m^{2*} because $f_m > a_L f_{a_L m}$. An increase in a_H always causes m^{2*} to increase.

$$\frac{dm^{*2}}{da_H} = (a_H)^2 \left(\frac{f_e f_{me} f_{kk} - f_e f_{ek} f_{mk} - f_k f_{me} f_{ek} + f_k f_{ee} f_{mk}}{\mid f \mid}\right) > 0$$

Therefore, for a sufficiently high a_H, it will be the case that $m^{*2} > m^{*1}(\theta)$.

Capital: The optimal level of capital usage is governed by:

$$f_k(a_L m^{*2}, a_H e^{*2}, a_H k^{*2}) = f_k(m^1(\theta), \overline{e}(\theta), k^1(\theta)) = p_k$$

An increase in a_H may cause k^{2*} to increase or decrease.

$$\frac{dk^{2*}}{da_H} = a_H \frac{\begin{array}{c} -a_L f_{ek} f_{mm}(k^{2*} f_{ek} + a_L f_e) + f_{mk}(f_e f_{me} - k^{2*} f_{mk} f_{ee}) + \\ -(a_L f_{mm} f_{ee} - f_{me} f_{me})(k^{*2} f_{kk} + f_k) \end{array}}{\mid f \mid}$$

Sufficient condition for $\frac{dk^{2*}}{da_H} < 0$:

$$(|k^{*2} \frac{f_{kk}}{f_k}| > 1)$$

So, if these conditions are met, then for a sufficiently high a_H, the optimal level of capital usage under technology 2 will lower than that under technology 1 ($k^{2*} < k^1(\theta)$).

Profits: The firm will switch from technology 1 to technology 2 when it is indifferent between using technology 1 and technology 2. Therefore, the profit of the firm will not change at the point that the firm switches between the two technologies. That is, $\pi^1(\theta) = \pi^{2*}$.

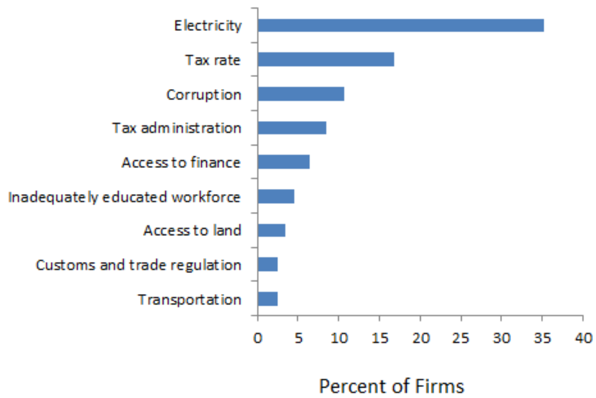
Output: To show that output of the firm will increase when it switches from technology 1 to 2, I use proof by contradiction.

Assume that output is lower under technology 2 than technology 1. That is, $y^1(\theta) \geq y^{2*}$. I show that this implies that $\pi^1(\theta) > \pi^{2*}$ (which is a contradiction).

$$\begin{aligned}
\pi^1(\theta) &= \int_{y=0}^{y=y^1(\theta)} (p_y - \frac{dC^1}{dy})dy \\
&= \int_{y=0}^{y=y^{2*}} (p_y - \frac{dC^1}{dy})dy + \int_{y=y^{2*}}^{y=y^1(\theta)} (p_y - \frac{dC^1}{dy})dy \\
&> \int_{y=0}^{y=y^{2*}} (p_y - \frac{dC^2}{dy})dy + \int_{y=y^{2*}}^{y=y^1(\theta)} (p_y - \frac{dC^1}{dy})dy \\
&\geq \pi^{2*}
\end{aligned}$$

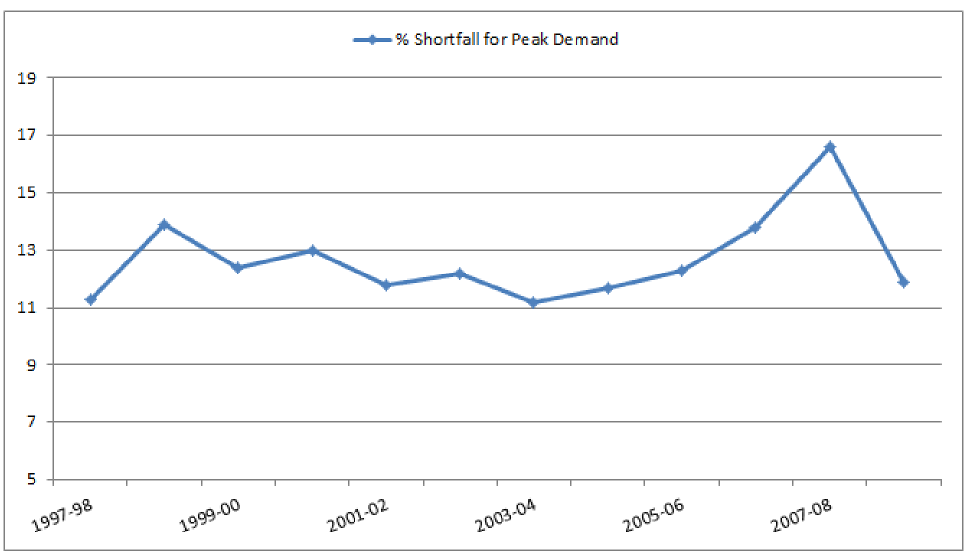
This contradicts that $\pi^1(\theta) = \pi^{*2}$. Therefore, it must be the case that $y^1(\theta) < y^{2*}$.

Fig. 2.— Top Business Environment Constraints



Source: Indian Enterprise Survey 2006, World Bank.

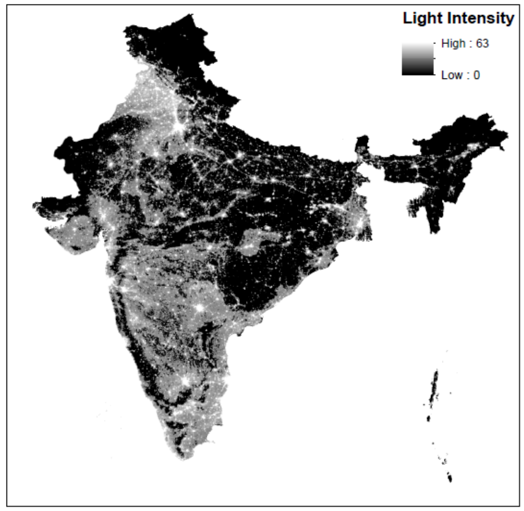
Fig. 3.— India: Shortfall of Electricity



Comment: These actual numbers for shortfall are heavily assumption driven. It is our analysis that the shortfall is higher, and even state government officials have publically stated shortfalls as high as 30% (shortfalls are region and time of year specific). This excludes any spinning reserves plus reserve margin, typically set at 15-20% in many countries.

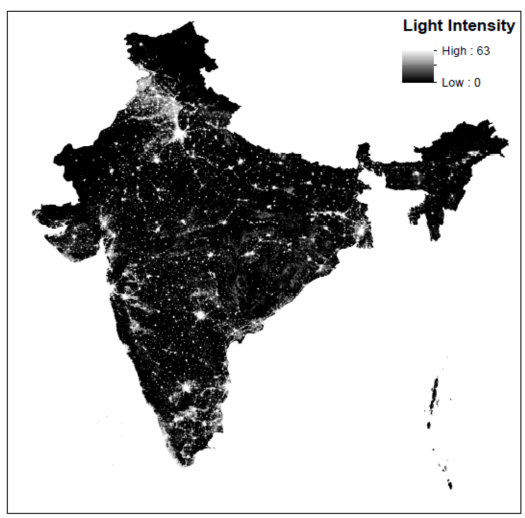
Source: Center for Study of Science, Technology and Policy (CSTEP), Bangalore, India.

Fig. 4.— Stable Lights in 2004



Source: Image and Data processing by NOAA's National Geophysical Data Center. DMSP data collected by the US Air Force Weather Agency.

Fig. 5.— Normalized Visible Lights in 2004



Source: Image and Data processing by NOAA's National Geophysical Data Center. DMSP data collected by the US Air Force Weather Agency.

Fig. 6.— Disrict Level Power Outages in 2004

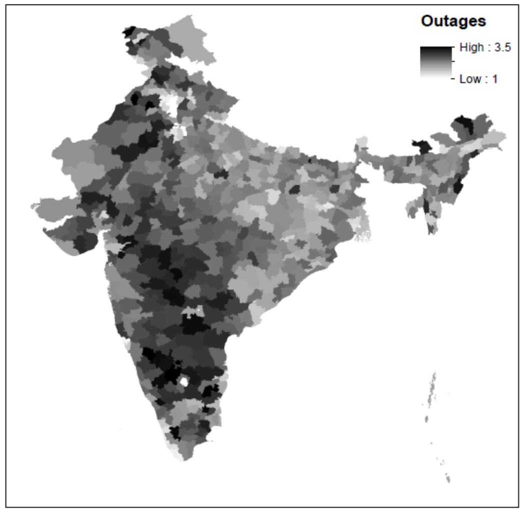


Image created using DMSP data collected by the US Air Force Weather Agency.

Fig. 7.— Disrict Level Variation in Power Outages between 2001-2008

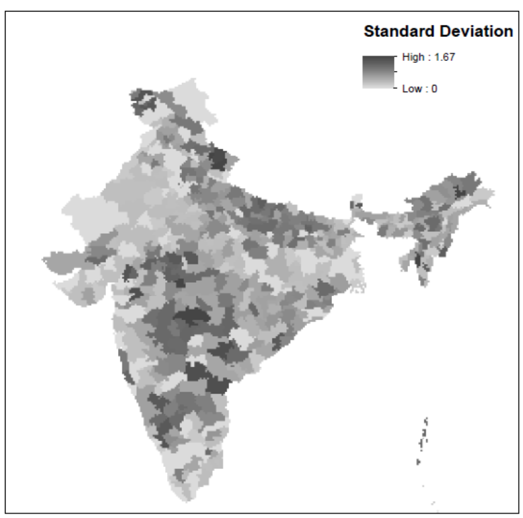
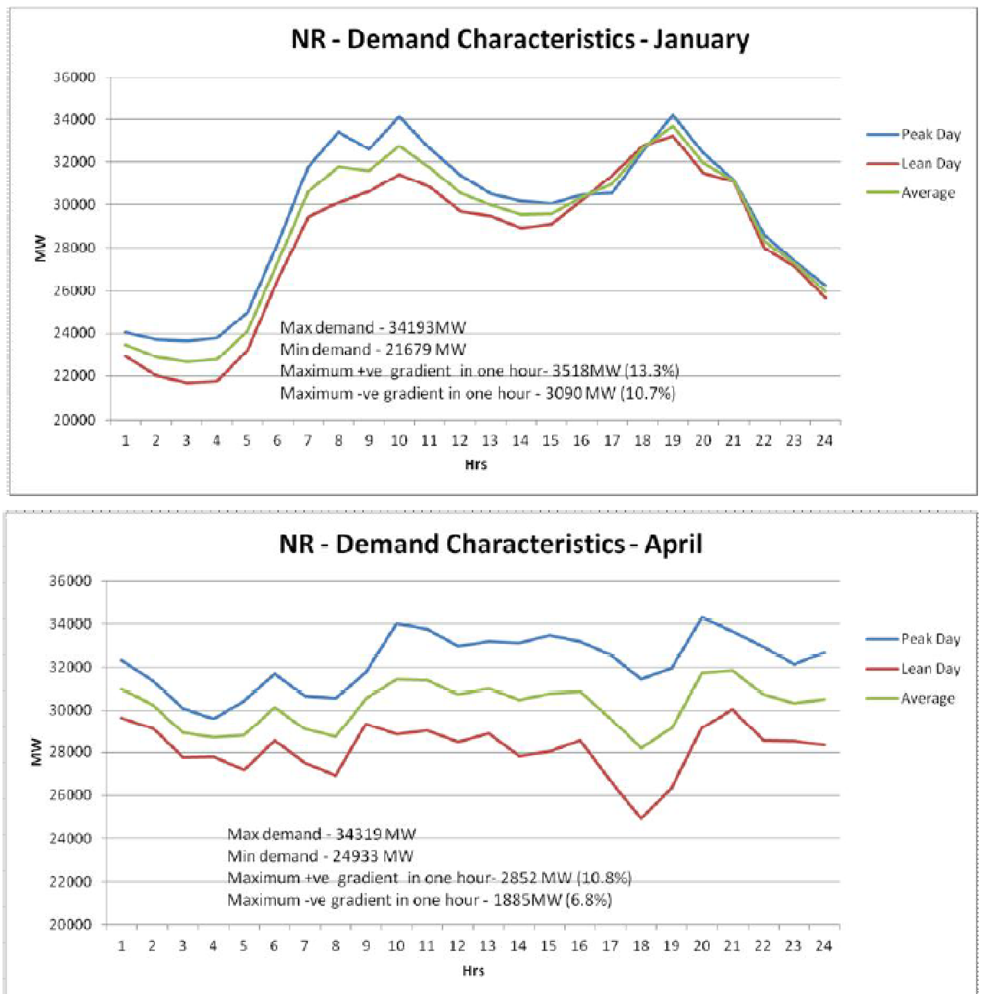


Image created using DMSP data collected by the US Air Force Weather Agency.

Fig. 8.— Trends in electricity demand in Northern Region, India



Source: Central Electricity Authority, Year: 2010

Table 1: Peak Demand (MW) and Energy Shortages as of 31 January 2005

Region	Peak Demand	Peak Met	Deficit	Percentage Deficit
Northern Region	25,095	22,316	2,779	11.07
Western Region	30,084	23,096	6,988	23.23
Southern Region	21,506	20,954	552	2.57
Eastern Region	8,489	8,371	118	1.39
North Eastern Region	1,272	995	277	21.78
All India	86,446	75,732	10,714	12.39

† Source: Yadav et al. (2005).

Table 2: Summary Statistics

	Bricks	Rice	Steel
No of firms	1,576	2,165	1,185
Capital	192,721	1,718,431	27,570,192
Electricity bought	3,355	177,665	2,675,181
Total electricity	3652	189,586	2,918,158
Own a generator	0.03	0.26	0.20
No. of months of operation	7.01	9.36	11.64
Quantity of input	13,279	3,806	6,739
Quantity of output	1,727	3,083	7,363

† The sample consists of districts in which I observe at least one brick kiln and at least one rice or steel mill. The value of capital is reported in Rupees. Electricity usage is reported in kilo-Watts. For rice/steel mills, both the input and output are reported in tonnes. For brick kilns, input (clay) and output (bricks) is reported in tonnes and thousands, respectively.

Table 3: Checking the validity of the power outage measure

	Percentage deficit of electricity	Irregular supply
Outages	5.23***	0.05***
	(1.44)	(0.01)
Obs	132	6259
R Sq	0.09	0.08

† Column 1 uses data from the Ministry of Power, India. Column 2 uses data from Rural Economic and Demographic Survey (2005-2006), India.

Table 4: Daytime and nightime power outages

	Percentage deficit of electricity
Irregular supply of electricity	0.65***
	(0.12)
Obervations	6259

† Data sources: Ministry of Power, India and Rural Economic and Demographic Survey (2005-2006), India.

Table 5: Power outages and rainfall

	Outages
Monsoon Rain	0.11***
	(0.012)
Total Rain	0.09***
	(0.02)
Obs.	4,293

† Rain is measured as deviation from historic mean. District fixed effects included.

Table 6: Electricity Usage

	Bought Electricity	Total Electricity	Bought Electricity	Total Electricity
Steel x Outage	-0.748**	-0.653**	-1.179**	-1.197**
	(0.292)	(0.282)	(0.557)	(0.576)
	[-9.95%]	[-8.68%]	[-12.97%]	[-13.17%]
Rice x Outage	-0.365*	-0.390**	-0.233	-0.229
	(0.203)	(0.193)	(0.441)	(0.443)
	[-4.85%]	[-5.19%]	[-2.56%]	[-2.52%]
Fixed-effects	district-year	district-year	district-industry	district-industry
Obs.	6,545	6,545	6,456	6,456

† Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the level of the fixed-effects.

Table 7: Power Outages and Profits

	(I)	(II)
Bricks x Outage	-2,031	-1,146
	(4,292)	(43,348)
Steel x Outage	-37,626**	-159,929*
	(15,681)	(80,284)
Rice x Outage	396	4,124
	(2,191)	(24,564)
Fixed-effects	district	district-industry
Obs.	4,589	4,589

† District fixed effects. Standard errors in parentheses. Standard errors are clustered at the level of the fixed-effect.

Table 8: Material usage

	(I)	(II)
Steel x Outage	-0.184	-0.020
	(0.183)	(0.973)
	[-2.45%]	[-0.22%]
Rice x Outage	0.580*	1.475*
	(0.326)	(0.777)
	[7.71%]	[16.23%]
Fixed-effects	district-year	district-industry
Obs.	3,881	3,860

† Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the level of the fixed-effects.

Table 9: Output

	(I)	(II)
Steel x Outage	-0.839***	-1.94**
	(0.332)	(0.919)
	[-11.16%]	[-21.34%]
Rice x Outage	0.010	0.287*
	(0.266)	(0.166)
	[0.13%]	[3.16%]
Fixed-effects	district-year	district-industry
Obs.	3,926	3,901

† Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the level of the fixed-effects.

Table 10: Generators and Capital

	Capital	Generators	Capital	Generators
Steel x Outage	-0.710*	0.042	-0.998	-0.053
	(0.381)	(0.337)	(0.879)	(0.533)
	[-9.44%]	[0.56%]	[-10.98%]	[-0.58%]
Rice x Outage	-0.464*	-0.085	-0.441	0.263
	(0.269)	(0.244)	(0.402)	(0.469)
	[-6.17%]	[-1.13%]	[-4.85%]	[2.89%]
Fixed-effects	district-year	district-year	district-industry	district-industry
Obs.	5,842	4,691	5,824	4,855

† Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the level of the fixed-effects.

Table 11: Intensive and Extensive Margin of Operation

	Months Operated	Operate	Months Operated	Operate
Steel x Outage	0.026	0.012	0.040	0.022
	(0.039)	(0.019)	(0.050)	(0.036)
	[0.35%]	[0.16%]	[0.004%]	[0.002%]
Rice x Outage	0.133***	0.007	0.064	0.037
	(0.041)	(0.018)	(0.053)	(0.024)
	[1.77%]	[0.09%]	[0.007%]	[0.004%]
Fixed-effects	district-year	district-year	district-industry	district-industry
Obs.	6,592	7,095	6,572	7,095

† Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the level of the fixed-effects.

Table 12: Power Outages and Relative Prices

	(I)	(II)
Steel x Outage	0.213	0.235
	(0.358)	(0.562)
	[2.83%]	[3.12]
Rice x Outage	-0.034	-0.052
	(0.341)	(0.229)
	[-0.45%]	[-0.69%]
Fixed-effects	district-year	district-industry
Obs.	4,293	4,293

† District-year fixed effects. Standard errors clustered at the district level. Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%.

Table 13: Electricity, and Generator Usage

	Bought Electricity	Total Electricity	Generator
Outage	0.619**	0.657***	0.297
	(0.244)	(0.246)	(0.251)
	[8.23%]	[8.74%]	[3.95%]
Steel x Outage	-0.679***	-0.605**	0.012
	(0.236)	(0.245)	(0.301)
	[-9.03%]	[-8.05%]	[0.16%]
Rice x Outage	-0.438*	-0.425*	-0.126
	(0.226)	(0.231)	(0.221)
	[-5.83%]	[-5.65%]	[-1.68%]
Obs.	6,600	6,600	5,760

† District fixed effects. Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the district level.

Table 14: Capital, Inputs, and Output

	Capital	Material	Output
Outage	0.755**	-0.314	0.188
	(0.357)	(0.359)	(0.209)
	[10.04%]	[-4.18%]	[2.50%]
Steel x Outage	-0.317	-0.196	-0.730***
	(0.381)	(0.320)	(0.281)
	[-4.22%]	[-2.61%]	[-9.71%]
Rice x Outage	-0.264	0.521*	0.071
	(0.271)	(0.301)	(0.214)
	[-3.51%]	[6.93%]	[0.94%]
Obs.	5,864	3,889	3,909

† District fixed effects. Standard errors in parentheses. Square brackets give the % increase in the outcome variable when mean of power outages increases by 10%. Standard errors are clustered at the district level.

Table 15: Robustness check: Log-linear model

	Capital	Material	Output	Generator
Steel x Outage	0.133	-0.029	-0.757**	0.022
	(0.3301)	(0.373)	(0.357)	(0.050)
Rice x Outage	-0.580***	0.778**	0.308	-0.020
	(0.168)	(0.326)	(0.292)	(0.026)
Obs.	5,842	3,881	3,926	6,614

† District-year fixed effects. Standard errors in parentheses. Standard errors are clustered at the district-year level. The equation for generator usage is estimated as a linear model.

Table 16: Robustness check: Electricity, and Generator Usage

	Bought Electricity	Total Electricity	Generator
Steel x Outage	2.077**	1.884**	0.430
	(0.832)	(0.799)	(0.675)
Rice x Outage	1.128*	1.240**	0.166
	(0.660)	(0.629)	(0.675)
Obs.	6,545	6,545	4,691

† District-year fixed effects. Standard errors in parentheses. Standard errors are clustered at the district-year level.

Table 17: Robustness check: Capital, Inputs, and Output

	Capital	Material	Output
Steel x Outage	1.673**	0.313	2.150***
	(0.775)	(0.834)	(0.785)
Rice x Outage	2.117**	-1.713*	0.005
	(0.920)	(0.905)	(0.816)
Obs.	5,842	3,881	3,926

† District-year fixed effects. Standard errors in parentheses. Standard errors are clustered at the district-year level.