Coping with Blackouts: Power Outages and Firm Choices

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ABSTRACT

Electricity shortage is a major constraint for Indian firms. In the World Bank Enterprise Survey manufacturing firms in India report that the typical power outage lasts 4 hours. Overall, power outages result in losses equivalent to 6.4% of annual sales. However, businesses can adjust their means of production to cope with power outages. The ability of firms to re-optimize creates significant heterogeneity in the impact of electricity shortage. In this paper, I study the consequences of inter-industry heterogeneity in adaptation to electricity shortages on a firm's productivity and profits. My analysis focuses on two important electricity intensive industries in India: rice and steel mills. I use meteorological satellite data to construct an objective measure for the frequency of power outages. I find evidence that unlike steel mills, rice mills are able to adjust to power outages by altering their input mix. My results indicate that increases in the frequency of power outages reduce the output and profits of steel mills but not rice mills. Overall, even within electricity intensive industries, there is significant heterogeneity in firms' ability to adapt to power outages; and therefore to their economic effects.

Keywords: Infrastructure, Electricity, Firm Choices, Private Investment

JEL: O18, D22

*I am extremely grateful to my advisors, Christopher Udry, Mark Rozenzweig, Mushfiq Mobarak, and Daniel Keniston, for their guidance and support. Thanks also to David Atkin, Costas Meghir, Nancy Qian, Larry Samuelson, Alex Cohen, Sabyasachi Das, Camilo Dominguez, Anne Guan, Melanie Morten, Adam Osman, Gabriella Santangelo, and participants at the Yale development lunch for many helpful comments and suggestions. Any remaining errors are my own.

1. Introduction

Underprovision of infrastructure is considered to be a key impediment to growth.[1] However, researchers have a limited understanding of how poor quality infrastructure affects the decisions of firms and businesses. Firms do not simply swallow the costs and consequences of inadequate infrastructure without adjusting their means of production. The scope of re-optimizing decisions both limits the adverse effects of poor infrastructure and creates significant inter-industry heterogeneity in their impacts. Improvements in infrastructure may have very different effects across industries; as a result, an uneven effect on economic growth.

This paper studies the consequences of inter-industry heterogeneity in adaptation to electricity shortages on a firm's productivity and profits in India. Despite the Indian government's commitment to bolster the country's electricity supply, the availability of reliable and cheap electricity remains a major challenge for India's industrial sector. In the World Bank Enterprise Survey, 35.2% of Indian firms cite electricity as the single biggest obstacle to business. Electricity is a bigger problem for these firms than tax rates, corruption, access to finance, transportation, etc.[2] India has never met its peak demand for electricity. Infrastructure development has not kept pace with the growing electricity needs of the consumers; the State uses demand side management to make up for the electricity deficit. As a result, power outages are frequent. South Asian firms report more than one outage per day of an average duration of 3.3 hours. For manufacturing firms in India, the typical outage lasts 4 hours and firms report that overall outages result in losses equivalent to 6.4% of annual sales.[3]

In my analysis, I focus on two important Indian industries that illustrate the consequences of differential industry-level adaptation to power outages: rice and steel milling. Rice milling is the biggest grain processing industry in India in terms of output. Similarly, steel making is also a salient industry in India: the steel sector contributes 2% to India's GDP. In 2010, India produced 68.32 MT crude steel and was ranked 4th largest steel producer in the world. Rice and steel mills use different adaptation mechanisms to cope with

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[1] Development of transportation networks has a positive level effect on GDP/ real income (Banerjee et al. (2012) and Donaldson (forthcoming)). Improvement in telecommunication reduces market inefficiencies by reducing information frictions (Jensen, 2007) . Access to electricity allows households to allocate more time to the labor market (Dinkelman, 2011) and has positive long-run effects on development indicators (Lipscomb et al., 2013). At the macroeconomic level, Calderon et al. (2011) estimate that a 10% increase in infrastructure provision is associated with a 1% increase in output in the long-run.

[2] See figure 2 for details.

[3] Source: Enterprise Survey (World Bank)

power outages. 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).[4]

My model allows electricity constrained firms to use both these adaptation channels when deciding on optimal levels of material usage and capital holdings. These choices determine output and profits. 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. Steel mills use less material, produce less output, and make lower profits. In contrast, the material usage and output of rice mills increases (profits stay the same) because they switch to the more electricity-efficient technology as power outages increase.

Most empirical studies use self-reported measures of power outages since gathering actual outage data is difficult. Self-reported measures are likely to be biased. I circumvent this problem by constructing a novel measure for the frequency of power outages using meteorological satellite data. Time-series data on nighttime lights at the same location allows me to quantify within-year variability in light intensity, and infer the frequency of outages.

My key empirical challenge is to control for variables outside the model that may influence both power outages and the business environment. For example, economic growth can be positively correlated with electricity shortage if the infrastructure is not able to keep up with the growing demand for electricity. Similarly, civil unrest 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 my analysis, I control for omitted variables at a fine geographic level of district. I match outage data to plants at the district level, and improve on prior research by exploiting triple-difference variation (district-time-industry) to estimate the effect of power outages on electricity-intensive rice and steel mills relative to electricity non-intensive brick kilns.

This paper is directly related 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. However, all these empirical attempts provide unreliable estimates because they either use self reported measures

[4]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).

of power outages and/or do not fully account for the correlation between economic growth and power outages. My estimation strategy eliminates both these sources of bias. More broadly, this paper is related to literature that assesses the impact of electricity availability and pricing on household choices, industrial productivity, and industrial composition.[5]

This paper makes three principle contributions to the literature. First, 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. Second, to my knowledge this is the first study that disentangles the effect of power outages from that of economic growth within a country. Third, this paper explores a neglected dimension of firms' responses to power shortages. Alongside examining the most direct first-order effects on generator usage, I also look at whether firms cope with power outages by switching to a technology that allows them to process more material in a given amount of time. I also assess whether firms cope with outages by operating for more days of the year.

I test the predictions of my model using plant level data for brick kilns, rice mills, and iron/steel mills 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 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 respectively from the public grid. 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 6.17% for rice mills. Variations in the intensity of power outages do not influence generator ownership. This is indicative of the high cost for generator installation.

Overall, rice mills are better able to adjust to power outages than steel mills. First, rice mills are able to adjust their production technology and substitute towards using more material inputs. In response to a 10% increase in outages, they use 7.71% more paddy. 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. This translates into lower profits.

The results of this paper have important policy implications. Industries can alter their input mix 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 heterogenous impact on the manufacturing sector. Some industries will be better able to adapt to power outages. Industrial sectors in which adaptation to power outages is not possible should be given priority electricity and/or

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

discounted generators.

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 useful 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 cause of the unreliability in electricity supply. For the industries, I provide details about the production processes and the different coping mechanisms that rice and steel mills can use to deal with power outages. These coping mechanisms will be guide the setup of the model in section 3.

2.1. Electricity Sector in India

The July 2012 blackout is indicative of the energy challenges that India faces. It was the largest blackout in history and left approximately 9% of the world population without power. Two important reasons behind 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). However, like most countries in this region, India spends too little on infrastructure. Between 2007-2012 India has only spent 5.7% to 8.3% of its GDP on infrastructure[6].

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 State charges

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

a different tariff to agricultural, commercial, domestic, and industrial consumers. Industrial consumers heavily cross-subsidize the electricity price for the other sectors. For example, 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 been consistently making losses. 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). While some States are better able to meet their electricity demands, unmet demand varies from one region to the other (table 1). This State-level variability implies that there is significant cross-district variation in the availability of reliable electricity. I use this variation across districts and time to estimate the effect of power outages.

Unsurprisingly, power outages are frequent in India. Firms in South Asia experience 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.[7] These self-reported measures indicate that unreliable supply of electricity is a major bottleneck for Indian firms.

2.2. Industry

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

Brick making is a leading non-electricity intensive industry in India. It uses coal or wood as the energy input in its production process, and is highly sensitive to economic growth. Therefore, it is an ideal industry for capturing the impact of economic growth on firm choices. Further, brick-making is a seasonal industry that operates in the dry season. The primary material inputs are clay and sand. Clay is mixed with water and made into bricks. The bricks are then fired in a kiln till they dry and harden. Once cooled, the bricks are ready for sale.

Rice milling is the biggest grain processing industries in India in terms of output. For example, in 2006, India produced 93350 (1000 MT) of processed rice as compared to only

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

69350 (1000 MT) of wheat.[8] 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 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 ready-to-cook rice. All three processes involved in rice milling are highly electricity intensive. Therefore, rice mills are highly dependent on electricity.

Rice mills tend to cope with power outages in two ways. First, they can install captive generators. Second, they can accelerate the production process and produce more output in the duration that they have electricity 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, since paddy is expensive rice millers prefer minimizing paddy breakage by running the two machines at a low speed for a longer duration of time. The mills can process rice as much as three times faster by running the machinery at a higher speed. But this increase in processing speed comes at the expense of significantly higher breakage of paddy. Thus, the rice to paddy ratio is lower if the mills handle the rice less delicately. I incorporate this in my model (section 3) by allowing the mills to choose freely between two different production technologies.

Similarly, steel making is also a salient industry in India. In 2010, India produced 68.32 MT 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 in which steel can be produced in India. These production methods can be broadly classified into three categories: Basic Oxygen Furnace (BOF), Electric Arc Furnace (EAF), and Electric Induction Furnace (EIF). The EAF AND EIF methods are highly electricity intensive with electricity consumptions of approximately 600 K-Wh/t and 500 K-Wh/t 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.[9]

In terms of electricity use, the key difference between EAF and EIF is the intensity of

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

[9]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).

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 business model that the firm wants to use.

Steel mills tend to cope with power outages in two ways. First, they can install generators.[10] While it is not economically feasible for most plants to shift production from publicly supplied electricity to power generated in-house, in case of power outages, firms can use generators to safely shut-off the plant. 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-a-day over the weekend to make up for some of the lost time.[11] Unlike rice mills, I did 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.

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[10]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.

[11]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.

3.1. Setup[12]

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.[13] If a firm is electricity constrained, then its electricity usage is denoted by $\overline{e}(\theta)$ (where $\frac{d\overline{e}(\theta)}{d\theta} < 0$). All the inputs are complementary ($\frac{\partial^2 f}{\partial x_i \partial x_j} > 0$ for $i \neq j \in \{m, e, k\}$). Economic growth enters the model via the prices. In conjunction with this, 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). The price of self generated electricity (p_e^H) is higher than that of electricity consumed from the public network (p_e^L). 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.

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 make the following assumptions about the two technologies. Firstly, compared to technology 1, technology 2 uses electricity and capital more efficiently ($\frac{\partial f(a_L \widehat{m}, a_H e.\widehat{k})}{\partial x_i} > \frac{\partial f(\widehat{m}, e.\widehat{k})}{\partial x_i}$ for $x_i \in \{e, k\}$). However, this comes at the expense of using materials less efficiently ($\frac{\partial f(a_L m, a_H \widehat{e}.\widehat{k})}{\partial m} < \frac{\partial f(m, \widehat{e}.\widehat{k})}{\partial m}$). Secondly, the marginal cost of producing output is higher under technology 2 than technology 1 ($\frac{dC^1(y)}{dy} < \frac{dC^2(y)}{dy}$). The data shows that rice mills' expenditure on paddy is 24 times that of electricity on average. Therefore, it is reasonable to assume that the increases 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

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[12] In the setup of the model, I do not superscript inputs, outputs or prices by type of firm for notational simplicity.

[13] p_m, p_k, and p_y denote the prices of material, capital, and output respectively; e denotes electricity usage; f denotes the production function.

capital to own, and how much materials and energy to use. Rice mills also decide between technology 1 and 2.

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). 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:

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

$\mid f \mid$ 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 steel mills 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 governed by $e = \overline{e}(\theta)$. As power outages increase, the the electricity usage decreases ($\frac{d\overline{e}(\theta)}{d\theta} < 0$). In this case the comparative static for material and capital usage is given by:

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

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.

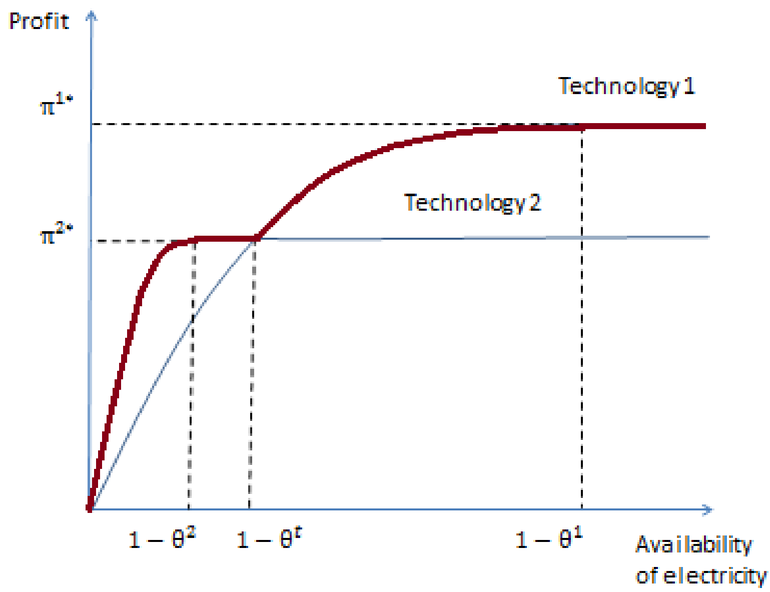
Rice Mills: In this section, I trace the input usage, output and profits of non-generator owning rice mills as power outages increase. I focus on the intuition for the predictions. The detailed proofs are provided in appendix 1.1. Rice mills choose between technology 1 and 2. Figure 1 traces out the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

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:

- 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 prediction and reasoning in section 3.2.2).

Fig. 1.— Profits and Outages



- As outages increase beyond $\theta = \theta^t$, the firm switches from technology 1 to 2. Profit remains unchanged. Since the firm is able to use electricity more efficiently, its output will increase. If a_H is sufficiently high, then the material usage of the firm will increase as well. In addition to a_H being large, if the marginal product of capital is highly responsive to the capital holdings of the firm, then the capital holdings of the firm will decrease.

- 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 $\theta > \theta^t$, 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 prediction and reasoning in section 3.2.2).

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

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

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

My model generates different predictions for rice and steel mills. 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 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. 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.

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.[14] Night-lights emanating from each location on Earth are observed by the satellite between 8:30pm and 10:00pm 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 within 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 sq km 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.

4.2. Construction of the Measure of Power Outage

I construct the measure of power outages at the district level. Night-light data has been used to study economic growth, poverty, and spatial apportionment of population[15], but to my knowledge, this is the first use of night-lights 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

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

[15]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).

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.[16] 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.[17] 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 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 holding is a dynamic process, it is going to depend on current as well as lagged power outages. Thus, for each year (t) in which I observe the firms, I take the average of the yearly power

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

[17] 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.

outage measure over the last three years[18] and treat this average as the measure of power outages that these firms face:

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

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 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.

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

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. Examples of such variables include, but are not limited to, economic growth and civil unrest. In order to control for these confounding variables, my estimation strategy relies on the differential response of rice/steel mills and brick kilns to power outages.

I first describe my main specification. The main specification allows me to flexibly controls for variables that are correlated with outages and influence the manufacturing sector. I then describe an alternative specification. The alternative specification allows me to explore the direction of the biases that result if omitted variables are not properly controlled for.

5.1. Main specification

To empirically test the model, I estimate the triple difference between electricity intensive and non-intensive industries across districts and time. By including district-time fixed effects, I am able 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 rice and steel mills relative to electricity non-intensive brick kilns. Since power outages do not directly impact the choices of brick kiln, I am able to identify the causal effect of power outages on the choices of rice and steel mills.

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:

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

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. The coefficient of interest is α_k^y: it estimates the effect of changes in outages on industry k relative to brick kilns for outcome variable y.

υ_k denotes fixed effects by industry and υ_{jt} denotes district-year fixed effects. 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.

Variables that are correlated with outages and impact the business environment of the three industries differently will bias my results. Such variables can operate via two channels: by differentially affecting the demand for output or the input markets. In my model all demand side shocks will operate via prices. To rule out this possibility, I will show in the empirical section that outages do not differentially influence prices faced by the three industries. A key variable that can differentially influence the input markets is rainfall. Rainfall will influence outages in two ways. First, electricity networks in development 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. This 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 power outages. Alongside influencing power outages, rainfall will also influence the input market for rice mills. Monsoon rainfall shocks obvious affect the yield of paddy, and therefore, have a direct impact on rice mills. I control for this direct impact of outages on rice mills by allowing for district level rainfall shocks to differently influence each industry. These interactions are denoted by (X_{jkt}).

The outcome variables are electricity bought from the public grid (e^p), total electricity usage (e^t), value of capital (k), material (m), output (f), and a dummy for generator ownership (g). I also look at whether firms adjust at the extensive or intensive margin of operation; that is, a dummy for whether the firm operates or not, and the number of months of operation are also included in the list of outcome variables.

For comparability across the three industries, I estimate the specifications in terms of percentage changes in the outcome variable. Therefore, α_k^y has the following straightforward interpretation: it is the percentage change in y for industry k due to a one unit increase in the measure of power outage. When I present my results I will interpret these coefficients with respect to a 10% increase in power outages at the mean. This corresponds to a per day increase of one hour in outages.

I estimate the model 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.[19] Furthermore, PPML yields consistent point estimates for a broad class of models; in specific, 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.[20] The use of PPML for continuous variables was first proposed by Gourieroux

[19]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.

[20]This method of estimation for the covariance matrix does not rely on the limiting poisson assumption of the equality of the mean of dependent variable and its variance.

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.

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

$$\pi_{ijt} = \upsilon_k + \gamma_k^y O_{jt} + d_{jt} + X_{jkt} + \varepsilon_{ijkt}$$

In this specification there is no excluded industry.

5.2. Alternative specifications

The second level of analysis is the district level. Here fixed effects control for differences in the average level of power outages and economic development 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:

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

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 the results for the effect of power outages on choices of firms. When presenting my results, I indicate the expected change in the outcome variable when power outages increase by 10%. At the mean, a 10% increase in power outage measure corresponds to power outages increasing by one hour everyday. I focus on the results of my main specification. 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 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 effects peak electricity deficit; the estimated coefficient is significant at 1% level of significance (table 3, column 1). Second, I correlate my measure of power outages with a question about the regularity of night time electricity from the REDS.[21] An increase in outages positively associated with irregularity of electricity supply at night time; the estimated coefficient is significant at 1% level of significance (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% level of significance. 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 daytime and they are susceptible to power outages.

6.2. Electricity and Generator Usage

Tables 6 presents the results for the effect of power outages on electricity usage and generator ownership of firms. Increased power outages result in rice and steel mills consuming less publicly provided 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, respectively, from the public grid.

Firms do not appear to be responding to changes in power outages by investing in self generating capacity. Rice mills only use self generated electricity if there is an imminent

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

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 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. The effect of power outages on electricity usage is not dissipated in the total electricity usage[22] of the firms. This is consistent with my institutional knowledge of the two industries: rice and steel mills only use self-generated electricity in extreme circumstances.

6.3. Capital, Inputs, Outputs, and Profits

Table 7 presents the results for the effect of power outages on capital holdings, material inputs, and output of firms.

Firms adjust their capital holdings in response to power outages. 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.

My model predicted that, depending on the domain of changes in power outages, it is possible that rice mills will respond to power outages by increasing their material consumption. My results indicate that rice mills adapt to power outages by switching to a more electricity-efficient technology that substitutes electricity with more material inputs. At the mean, a 10% increase in power outages results in rice mills using 7.71% more paddy. My field visits indicated that steel mills cannot alter their technology in response to power outages. This is confirmed in my results: power outages affect the material usage of steel mills negatively, but the coefficient is not significant.

Increases in the frequency of outages do not induce steel mills to adapt by installing generators. Therefore, I expect the consequences of increases in power outages to be substantial. My results confirm that steel mills produce less output and are less profitable as the frequency of power outages increases. A 10% increase in the mean level of power outages results in a 11.16% decrease in output produced by steel mills. The profits made by steel mills are also substantially lower (table 8). Even though rice mills do not respond to increases in power outages by installing generators, increase in material usage suggests that they adapt by switching to a more electricity-efficient technology. So output and profits of rice mills remain unaffected by variations in power outages. My results suggest that rice mills are able to mitigate the consequences of power outages by adjusting their production

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

technology.

6.4. 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 not operate. 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 firms alters with changes in power outages. Steel mills are all-year enterprises while rice mills are seasonal enterprises. I find that a 10% increase in the mean level of power outages results in rice mills operating for 1.77% more months (table 9). This means that rice mills operate for 5 more days every year. This makes up for a third of the time that these firms loose 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 some firms that have temporarily stopped operating. In the short-run firms do not find evidence that firms shut down in response to power outages (table 9).

6.5. Alternative specification

The direction and magnitudes of the effect estimated in the alternative specifications are very similar to those estimated in the main specification. The results are presented in tables 11 and 12. 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 the size of rice and steel mills actually increases with power outages.

6.6. 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 for the three industries is different. 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 10, I check for the co-movement of relative prices and power outages[23] and find no evidence of prices moving in tandem with power outages at the district or district-year level . Therefore, my results are not driven by relative prices.

7. Robustness checks

To check for the robustness of my results I estimate two alternative specifications. 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 13. 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 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 14 and 15 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 that Indian firms make in two important industrial sectors: rice and steel mills. I have allowed firms to use industry specific adaptation mechanisms and traced the effects of power outages on firm size, productivity, and profits for rice and steel mills in India. I have also analyzed second order adjustments that firms can make by adjusting their material inputs usage and by altering their 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

[23]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. So the price of material inputs is the most relevant input price.

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 outages do not induce firms to adapt by installing generators. The lack of responsiveness of generator ownership to electricity shortage is consistent with anecdotal evidence from my field visits. Generally, rice mills use self-generated electricity if there is an imminent deadline and steel mills use self generated electricity to safely shutdown the plant. My results show that rice mills adapt to changes in power outages in two important ways. Rice mills adjust to outage by substituting electricity for more material inputs and are able to 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 will have a modest effect on industrial output. Second, improvements in electricity infrastructure will have heterogenous 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.

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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 if θ is such that firms are electricity constrained for both technologies, then firms will choose technology 2.

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

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

Electricity is more productive in technology 2. Therefore,

$$a_H f_{a_H e}(a_L m^{*2}, a_H \overline{e}, a_H k^{*2}) > f_e(a_L m^{*2}, \overline{e}, a_H k^{*2})$$

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,

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

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.[24]

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:

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

[24] 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.

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

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:

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

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

$$f_{ek} \to 0, f_{mk} \to 0, (|k^{*2} \frac{f_{kk}}{f_k}| < 1)$$

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, $\pi^{*1}(\theta) = \pi^{*2}(\theta)$.

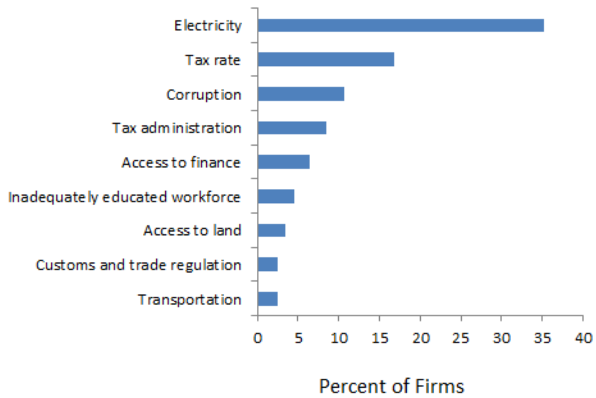
Output: To show that output of the firm will increase when it switches from technology 1 to 2, I use proof by contradiction.

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

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

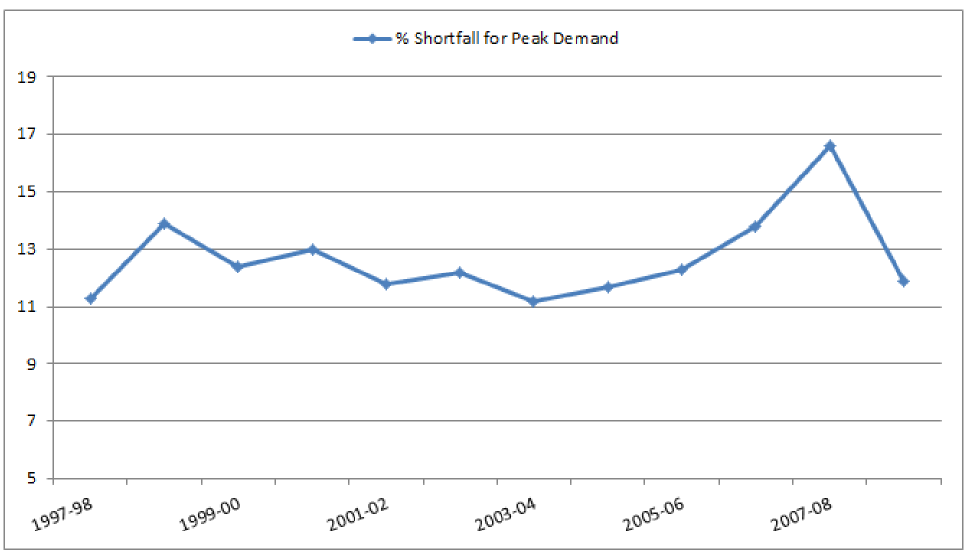
This contradicts that $\pi^{*1}(\theta) = \pi^{*2}(\theta)$. Therefore, it must be the case that $y^1(\theta) < y^2(\theta)$.

Fig. 2.— Top Business Environment Constraints



Source: Indian Enterprise Survey, World Bank.

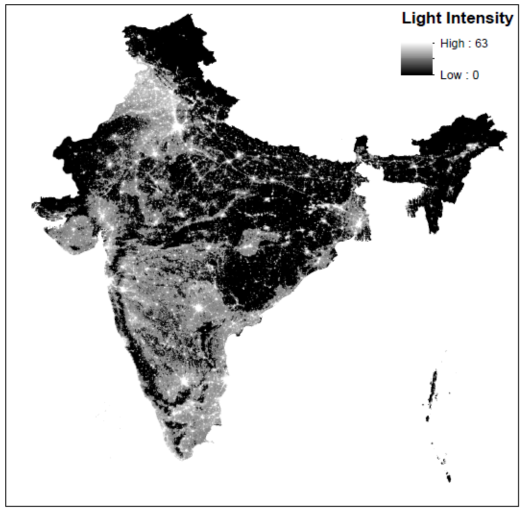
Fig. 3.— India: Shortfall of Electricity



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.

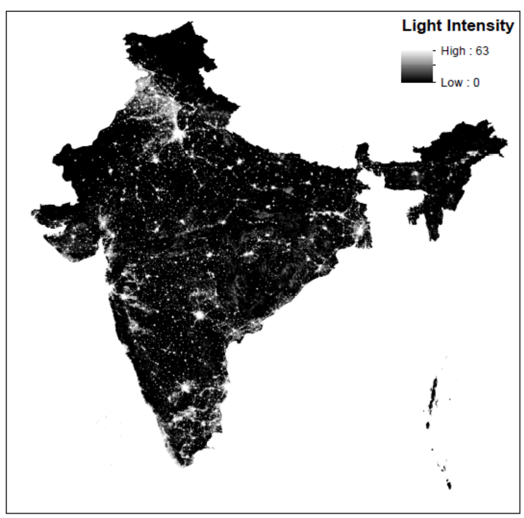
Source: Center for Study of Science, Technology and Policy (CSTEP), Bangalore, India.

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

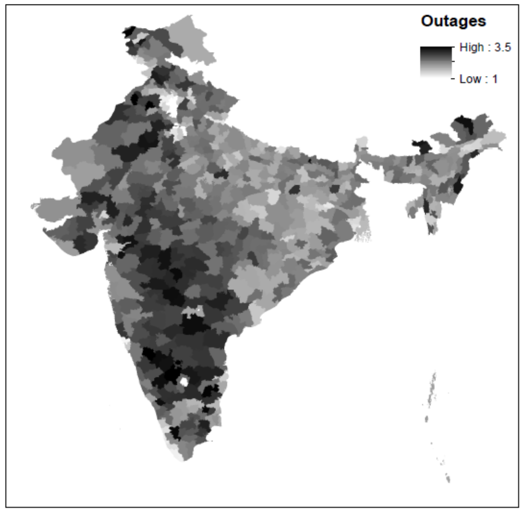


Image created using DMSP data collected by the US Air Force Weather Agency.

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

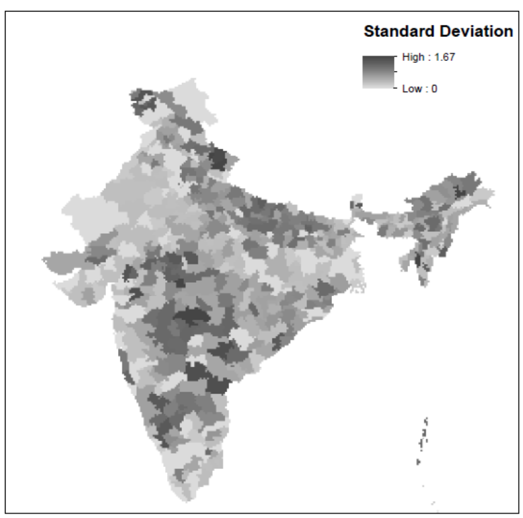
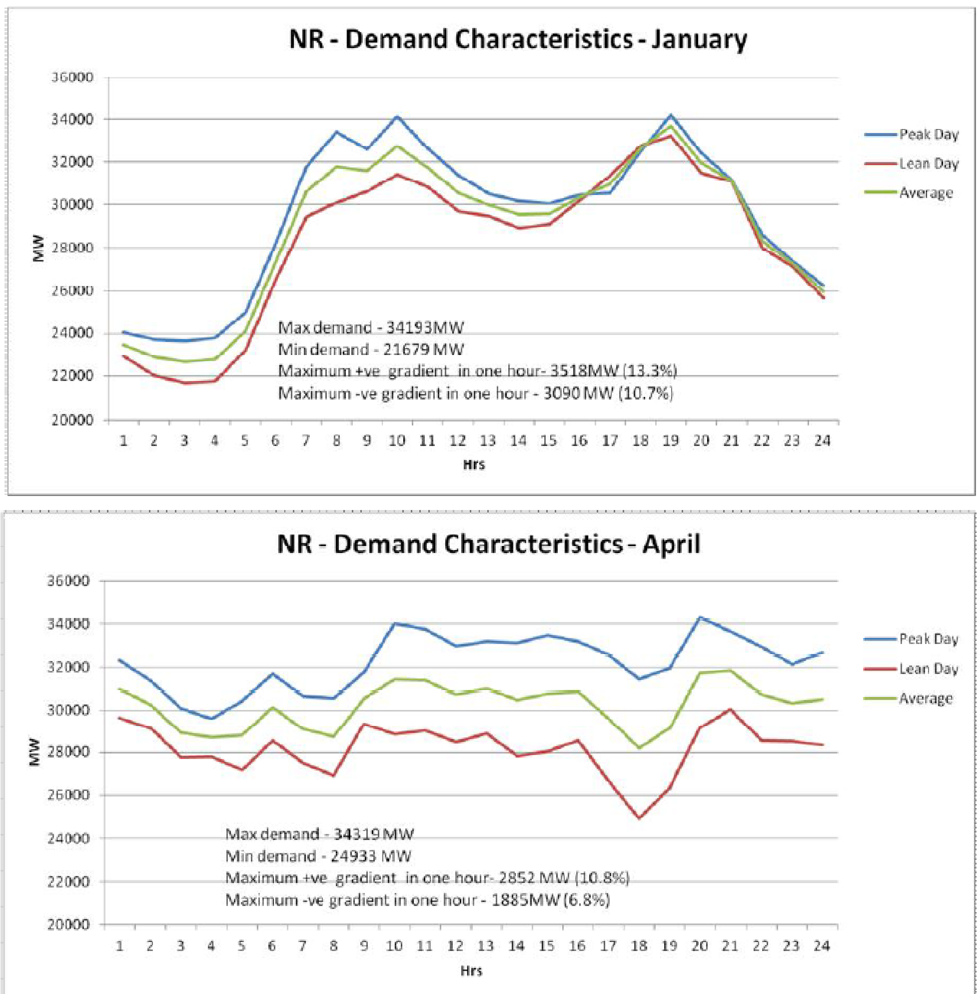


Image created using DMSP data collected by the US Air Force Weather Agency.

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)
Obervations	132	6259

† 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, and Generator Usage

	Bought Electricity	Total Electricity	Generator
Steel x Outage	-0.748**	-0.653**	0.042
	(0.292)	(0.282)	(0.337)
	[-9.95%]	[-8.68%]	[0.56%]
Rice x Outage	-0.365*	-0.390**	-0.085
	(0.203)	(0.193)	(0.244)
	[-4.85%]	[-5.19%]	[-1.13%]
Obs.	6,545	6,545	4,691

† District-year 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-year level.

Table 7: Capital, Inputs, and Output

	Capital	Material	Output
Steel x Outage	-0.710*	-0.184	-0.839***
	(0.381)	(0.183)	(0.332)
	[-9.44%]	[-2.45%]	[-11.16%]
Rice x Outage	-0.464*	0.580*	0.010
	(0.269)	(0.326)	(0.266)
	[-6.17%]	[7.71%]	[0.13%]
Obs.	5,842	3,881	3,926

† District-year 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-year level.

Table 8: Power Outages and Profits

	Profit (in 1000 rupees)
Steel	95,753***
	(21,688)
Rice	1,816
	(5,120)
Bricks x Outage	-2,031
	(4,292)
Steel x Outage	-37,626**
	(15,681)
Rice x Outage	396
	(2,191)
Obs.	4,589

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

Table 9: Intensive and Extensive Margin for Operating

	Months Operated	Operate
Steel x Outage	0.026	0.012
	(0.039)	(0.019)
	[0.35%]	[0.16%]
Rice x Outage	0.133***	0.007
	(0.041)	(0.018)
	[1.77%]	[0.09%]
Obs.	6,592	7,095

† District-year 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-year level.

Table 10: Power Outages and Relative Prices

	Relative Price
Steel x Outage	0.213
	(0.358)
	[2.83%]
Rice x Outage	-0.034
	(0.341)
	[-0.45%]
Obs.	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 11: 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 12: 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 13: 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 14: 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 15: 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.