How Do Electricity Shortages Affect Productivity? Evidence from India

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Abstract

In the World Bank Enterprise Survey, Indian business managers rate electricity supply as the single largest impediment to growth. We develop a production function model that highlights the two short-run effects of electricity shortages on industrial production. The *Shutdown Effect* is that when plants shut down during shortages, they waste non-storable inputs. The *Input Cost Effect* is that when plants continue to operate during shortages using backup generators, the backup generators are less efficient than utility-scale generation, and this increases total costs. We estimate these effects using detailed information on daily output and scheduled power holidays at a sample of textile plants, using data shared by Bloom et al. (2013). We also calibrate the model to the entire Indian manufacturing sector using the Annual Survey of Industries. The results are remarkable: despite the substantial perceived problems generated by power cuts, we estimate relatively small losses. Intuitively, the Input Cost Effect is small because the electricity input cost share in most industries is small, while the Shutdown Effect is small because the bulk of inputs are storable.

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1 Introduction

One of the potential contributors to the large productivity gap between developed and developing countries is low quality infrastructure, and one of the most stark examples of infrastructure failures is electricity supply in India. In the summer of 2012, India suffered the largest power failure in history, plunging 600 million people into darkness for two days.[1] However, even under normal circumstances, the Indian government estimates shortages of about 10 percent of demand at current prices, and many consumers have power only a few hours a day. As shown in Table 1 using data from a World Bank Enterprise Survey conducted in 2005, one-third of Indian firms name poor electricity supply as their biggest constraint on growth. This far outstrips other barriers frequently studied by development economists, including taxes, corruption, credit, regulation, and low human capital.

In this paper, we estimate the short-run effects of electricity shortages on manufacturing productivity in India. In this context, one prior is that because production is essentially Leontief - most factories cannot produce anything without electricity for lights, motors, and machines - shortages could significantly reduce output. On the other hand, precisely because the potential productivity losses would be so large, firms could purchase generators or develop other substitutes for electricity from the grid. Thus for manufacturing plants that have made investments into a backup power supply, the gains from reducing shortages could be small.

There are three reasons why this question is difficult. First, the standard production function model needs to be adapted for the case of input shortages, when firms cannot procure electricity for a part of the year. Second, the necessary data are difficult to acquire: industrial surveys may not have useful questions on electricity use, and more detailed firm-level datasets are not representative. Meanwhile, countries that have electricity shortages are the same types of countries that do not record or disclose data on the performance of public infrastructure. Third, shortages are not exogenous to productivity: rapid economic growth could cause an increase in power demand that leads to shortages. Alternatively, poor institutions that lead to insufficient power supply could also be at the root of power shortages. These two examples would bias causal estimates of shortages - albeit in opposite directions.

We begin with a set of stylized facts about electricity shortages and industrial electricity use in India. First, shortages occur both in high-GDP states, spurred by a difficulty in keeping up with economic growth, and low-GDP states, spurred by poor public sector management. Second, there is significant variation in shortages within states over time (from zero to 35 percent), driven by weather, coal shortages, fluctuating hydroelectric production, and other factors. Third, Indian manufacturers self-generate approximately 35 percent of their electricity. Fourth, self-generation is sharply increasing in plant size: while only about 10 percent of plants with fewer than 10 employees self-generate, about 60 percent of plants with more than 500 employees do so. Fifth, however, both

[1] See "2nd Day of Power Failures Cripples Wide Swath of India", July 31, 2012, The New York Times.

large and small establishments with and without generators report that electricity shortages are responsible for large losses of between five and eight percent of revenues.

We then present a production function model in which output is Leontief in electricity and a Cobb-Douglas aggregate of materials, capital, and labor. When grid electricity is unavailable, plants with generators can substitute to self-generated electricity at higher cost, and this acts similarly to an output tax. All plants without generators shut down, causing a loss of non-storable inputs. There are thus two major channels through which shortages affect manufacturers: an *input cost effect*, the substitution to higher-cost self-generated electricity, and a *shutdown effect*, due to the loss of non-storable inputs such as capital stock.

The empirical analysis begins with a case study of textile manufacturers in Gujarat and Maharashtra, using data shared by Bloom *et al.* (2013). These plants face pre-scheduled "power holidays" once each week, and they respond either by self-generation (incurring the input cost effect) or by shutting down and leaving the plant idle. While these data include only 22 plants, all of which have generators, they give very clean estimates of the input cost and shutdown effects, which are actually quite small: a 1.1 percent output loss, which translates into a 0.21 percent TFP loss.

We then broaden our scope to all manufacturing plants nationwide using the Annual Survey of Industries (henceforth ASI). We use a difference estimator, exploiting changes in shortages within states over time. To address the potential endogeneity of shortages - for example, economic growth both increases manufacturing output and worsens shortages - we instrument with changes in electricity production from dams, which are driven by changes in water inflows to reservoirs. For plants that own generators, a one percentage point increase in shortages causes a 0.8 percentage point increase in self-generation, which raises total input costs by 0.2 to 0.4 percentage points. We also find that shortages cause statistically significant decreases in output and productivity, although the confidence intervals include a wide range of effect sizes.

We then use simulations to more precisely identify effects on output, productivity, and the firm size distribution. We simulate the short-run effects of eliminating shortages for one year, holding constant capital stock. Across all firms, output and productivity increase by 6.5 and 1.2 percent, respectively. For plants that own generators, the input cost effect from self-generation lowers output by less than one percent. For plants that do not, however, the output loss is almost 10 percent.

The intuition behind this effect is the following. For plants that have backup generation capacity, electricity is both a small share of input costs and generated power is about twice as costly as power purchased from the grid. Thus, for plants that have generators, we should see fairly little response to shortages. On the other hand, for plants without backup generators, the effect of shortages can be large since these plants are offline during an outage. Yet the loss in TFP is moderate, as most of the inputs used in production are not wasted during an outage since most intermediate materials can be preserved until the shortage is over.

We use the empirical estimates and simulations for two extensions that connect to basic questions in the development economics literature. First, we ask how electricity shortages affect the

size distribution of industry. We find that eliminating shortages would increase the rate of return on capital by up to 30% percentage points for the smallest plants, versus less than 1% for large plants. Second, we estimate the average returns to investing in generators. We find that purchasing complete backup generation capacity would pay for itself in under three months, leading to the puzzle of why firms choose not to have generators.

The remainder of this section discusses related literature. Section 2 gives stylized facts on the Indian electricity sector and the causes of electricity shortages. Section 3 details the production function model. Section 5 is the case study of textile manufacturing in western India, using data from Bloom *et al.* (2013). Section 6 presents the ASI data and nationwide analysis. Section 7 details the counterfactual simulations, and Section 8 concludes.

1.1 Related Literature

This paper is related to a long literature that estimates the effects of investment in electricity, transportation, and other infrastructure. One set of papers examines the effects of infrastructure investment on growth in panel data from U.S. states: Aschauer (1989), followed by Holtz-Eakin (1994), Fernald (1999), Garcia-Mila, McGuire, and Porter (1996), and reviewed by Gramlich (1994). Easterly and Rebelo (1993), Esfahani and Ramirez (2002), and Roller and Waverman (2001) do similar analyses using cross-country panels. Hulten, Bennathan, and Srinivasan (2006) argue that growth of road and electricity generating capacity accounts for a remarkable 50 percent of productivity growth in Indian manufacturing between 1972 and 1992.

This literature has faced two basic problems. First, infrastructure spending is econometrically endogenous to economic growth. There could be reverse causality: fast growth increases tax revenues, which allow more infrastructure spending. There is also economic endogeneity: infrastructure may be specifically allocated to locations that are growing more quickly or slowly. Second, using infrastructure spending or quantities on the left-hand-side makes it difficult to distinguish between different types of infrastructure and the performance thereof. For example, our study highlights that spending on power plants does not necessarily translate into electricity provision.

Our paper is part of a recently-growing literature that evaluates the effects of infrastructure by combining within-country variation generated by natural experiments with household-level, firm-level, or district-level outcome data. Banerjee, Duflo, and Qian (2012) and Donaldson (2012) study the effects of railroads in China and India, Duflo and Pande (2007) study irrigation dams in India, Jensen (2007) studies information technology, and Baisa, Davis, Salant, and Wilcox (2008) study the benefits of reliable water provision in Mexico. Chakravorty, Pelli, and Marchand (2013), Dinkelman (2011), Lipscomb, Mobarak, and Barham (2013), Rud (2012a), and Shapiro (2013) study the effects of electricity grid expansions. A large literature studies firms' decisions of whether to invest in generators: Alby, Dethier, and Straub (2011), Foster and Steinbuks (2009), Steinbuks (2011), Steinbuks and Foster (2010), Reinikka and Svensson (2002), and Rud (2012b). Cropper, Limonov, Malik, and Singh (2011) and Ryan (2012) study other aspects of electricity supply and

demand in India.

Our paper is most conceptually and geographically related to three papers. Abeberese (2012) tests how changes in electricity prices affect productivity of Indian manufacturing plants. Another closely-related paper is Fisher-Vanden, Mansur, and Wang (2012), who show that Chinese firms switch to producing energy-intensive inputs, but do not produce more of their own electricity, in response to blackouts. Zuberi (2012) estimates a dynamic model of manufacturing production using data from Pakistan, showing how firms re-allocate production to periods when there are not shortages.

Foster and Steinbuks (2009), Zuberi (2012), and some other studies based on microdata argue that the cost of own-generation is small relative to total manufacturing revenues, suggesting that the benefits to manufacturing from improved electricity supply are small. By contrast, Hulten, Bennathan, and Srinivasan (2006) suggest that the benefits of spending on electricity infrastructure are large, at least over their sample period. We are not aware of any paper that has attempted to resolve this basic disagreement by estimating the effects of shortages on manufacturing productivity, as we do here. Thus, while there are many related papers and our three questions seem fundamental, they are still unanswered.

2 Stylized Facts

In this section, we provide a background on electricity shortages in India. We begin by presenting the data sources and an overview of electricity market structure in India. We then discuss systemic reasons for shortages and reasons for annual variation in shortages. Finally, we give background on industrial electricity use in India.

2.1 Power Sector Data

Our power sector data are from India's Central Electricity Authority (CEA). Many of the same types of data available online from the U.S. Energy Information Administration are also collected by the CEA. In practice, however, the online data are incomplete, and the hard copies of some printed materials have been misplaced, so data have to be collected from CEA staff. With the cooperation of CEA management and the help of research assistants in New Delhi, we were eventually able to compile, digitize, and clean about 25 years of data for this and related projects. Table 2 details these power sector variables and other state-level data.

The primary measure of electricity shortages is the percent energy deficit reported in the Load Generation Balance Report. Analysts at CEA and Regional Power Committees estimate the quantity that would be demanded for each state and month at current prices in the absence of shortages. This is summed over months to arrive at annual totals for each state. Our shortage measure is the percent difference between this counterfactual quantity and the quantity actually supplied. In alternative specifications, we also use a measure of "Peak Shortage", which is the average over

months of a state's difference between counterfactual peak quantity demanded (in megawatts) and actual peak quantity available.[2]

From an annual report called the Review of the Performance of Hydro Power Stations, we observe inflows into reservoirs behind 22 major dams covering about 40 percent of national hydro-electric capacity. From the CEA's annual General Review, we observe each state's total annual electricity generation for each technology, including hydroelectric plants. From the General Review, we also collected total quantity of electricity sold by utilities to end users for each state and year.

2.2 Overview of the Power Sector

As of February 2013, India had 214 gigawatts of utility-scale power generation capacity, or about one-fifth the US total (CEA 2013). Of this, 58 percent was coal, nine percent was natural gas, and 18 percent was hydro-electric. While power generation has been open to private investment since 1991, 70 percent of electricity supply remains government owned: 40 percent is owned by state governments, and 30 percent is owned by central government entities.

2.3 Reasons for Systemic Shortages

Power shortages, i.e. blackouts or "power cuts", are common in India. The Central Electricity Authority (2012) estimates that over the April 2011-March 2012 fiscal year, nationwide demand at current prices exceeded quantity supplied by 79,000 gigawatt-hours (GWh), or 8.5 percent. Peak quantity demanded at current prices exceeded available peak supply by 10.6 percent. Of course, this is not unique to India, nor is it new. During the 1992-1993 fiscal year, there was an 8.3 percent average shortage, and a 20.5 percent peak shortage.

The proximate systemic reason for shortages is that the distribution companies do not raise retail prices in order to clear the market. In fact, conditional on state and year effects, there is no correlation between the median electricity price paid by ASI plants and the shortage, nor in the annual differences. Aside from being stark evidence on how prices do not adjust to supply and demand conditions, this also means that the effects we estimate are caused by input shortages, not by input price changes.

There are several underlying systemic reasons for shortages. The first is the "infrastructure quality and subsidy trap" (McRae 2009): retailers provide low-quality electricity to consumers, who tolerate poor service because they pay very low prices. The retailers' losses from low prices are covered by government subsidies, and politicians do not remove the subsidies because voters would protest. In the Indian context, the SEBs have since at least the 1970s offered un-metered electricity at a monthly fixed fee and zero marginal cost to agricultural consumers, largely to run well pumps (Bhargava and Subramaniam 2009). In 2010, the national average retail electricity cost paid by agricultural consumers was 1.23 Rupees per kilowatt-hour (Rs/kWh), against Rs 4.78 for

[2]The two series are highly correlated, with an R^2 of 0.53.

industrial consumers and 3.57 Rs/kWh for all consumers. (The exchange rate is about 50 Rupees per dollar, and the average electricity price across all consumers in the United States is about 10 cents/kWh.) Although it would be difficult to compute the optimal prices for power, agricultural electricity is almost certainly under-priced.

Distortions in pricing are relevant only for consumers who actually pay for electricity. Twenty-six percent of electricity generated in India in 2010-2011 was lost due to theft or poor transmission infrastructure, down from 34 percent in 2004-2005. This means that the distribution companies have no ability to charge any price, let alone raise prices, on a significant share of production.

Agricultural subsidies and non-payment have led to mounting losses. The SEBs receive large annual payments from state governments to cover these losses, and in particular to fund the subsidies for agricultural consumers, but these payments and the cross-subsidy from industrial customers are not sufficient to cover the SEBs' costs. Between 1992 and 2009, the SEBs lost $54 billion dollars (again, in real 2004 dollars). These mounting losses caused the SEBs to reduce infrastructure investment, and degraded infrastructure further increases the probability of blackouts. The SEBs are bailed out at irregular intervals by the government.

A second systemic reason for shortages is underinvestment in new generation capacity. For example, after the 1991 liberalization, 200 Memoranda of Understanding were signed between the government and investors to build 50 gigawatts of generation capacity, but less than four gigawatts of this was actually built (Bhargava and Subramaniam 2009). Of the 71 gigawatts of capacity targeted to be built between 1997 and 2007, only half was actually achieved (CEA 2013a). Potential power plant investors faced concerns over both output demand and input supply. Their main customers, the State Electricity Boards, faced serious financial problems, and it was not clear that they would be able to honor contracts. Meanwhile, the main supplier of coal is Coal India, a government-owned monopoly that is struggling to keep up with demand growth.

Furthermore, the existing capacity is systematically underutilized. Between 1994 and 2009, Indian coal power plants were offline about 28 percent of the time due to forced outages, planned maintenance, or other factors such as equipment malfunction, coal shortages, or poor coal quality.[3]

One potential solution to problems with retail distribution companies is "open access": allowing consumers to contract directly with generators. The 2003 Electricity Act mandated open access, but in practice direct power sales to bulk consumers have not materialized (GOI 2009, 2012), partially because states have imposed additional charges on open access consumers and have also banned export of power to open access consumers in other states.

2.4 Variation in Shortages across States

These systemic factors differ across states, generating differences in shortages. A substantial part of these differences persist across years. Figure 1 shows a map of average shortages by state from

[3]We thank the authors of Cropper et al. (2013) for sharing their coal plant outage data with us. Our original intent was to use these outages as an instrument for shortages, but the first stage is not sufficiently powerful.

1992-2011, with higher-shortages states colored darker. Jammu and Kashmir was the highest-shortage state at 23 percent, followed by Bihar, Arunachal Pradesh, Uttar Pradesh, and Madhya Pradesh, respectively. Lakshadweep had zero shortages, and the next four lowest-shortage states were Chandigarh, Himachal Pradesh, Delhi, and West Bengal, respectively.

Figure 2 shows that there is a negative association between per capita GDP and electricity shortages. This suggests that low levels of development are associated with poor institutions, bad management, and other factors that worsen provision of public infrastructure.

2.5 Variation in Shortages over Time

There is substantial variation in shortages within states over time. Figure 3 shows the time path of annual average shortage over our sample for five large states. West Bengal has had consistently low shortages for the past 20 years. Maharashtra, which is now one of the highest-shortage states, had only small shortages in the early 1990s. Karnataka, which faced almost zero shortage in the mid-2000s, had significant shortages in the early to mid 1990s. Gujarat has reliable power supply now, but in the mid-2000s was experiencing shortages.

Several factors drive year-to-year fluctuations in shortages. On the demand side, fast or slow economic growth over a few years can increase or decrease shortages. In addition, low rainfall in a given year can increase farmers' utilization of groundwater pumps, which can markedly increase electricity demand. On the supply side, the electricity market is still small enough that individual plants can affect the aggregate supply-demand balance. Power plant outages for maintenance or due to fuel shortages can cause electricity shortages, and new plants coming online can temporarily reduce shortages. Later in the paper, we will discuss two other factors that cause annual variation in shortages, and satisfy the first stage and exclusion restriction requirements to be used as instrumental variables: variation in hydroelectric production due to low rainfall in the south and low snowpack in the north, and variation in annual average temperatures, which affect electricity demand to cool buildings. Table 2 presents summary statistics on the major state-level variables used in the analysis.

2.6 Industrial Electricity Use in India

A natural response to power shortages is for plants to purchase generators that are turned on during power outages. Indeed, manufacturing plants in India generate 35 percent of the power that they consume - quite a large share.

Figure 4 compares manufacturing electricity generation in India to the United States. Each dot reflects a 3-digit NIC code using data from the ASI described in more detail in section 5.1, which is used to match the industry to data from the US Manufacturing Energy Consumption Survey.[4] The

[4]Several industries don't match well between the two datasets: chemicals and refining are not broken out into many different sub-industries in the public US data, so Indian sub-industries such as Explosives, Chemicals Not

figure highlights two important facts. First, there is a strong correlation between the US and Indian data, suggesting that the data on generation in the ASI are meaningful. Indeed, many sectors in the United States – where power outages are presumably a second order issue – produce a large share of their power. For instance, in the sugar refining industry, the leftovers from processing sugarcane are often burned to produced electricity, so there is a natural complementarity between electricity generation and other activities. There are a number of industries in India with very large amounts of generation relative to the US. For instance, the Plastics Industry in the United States produces none of its power, while in India, this industry produces 70% of the electric power it uses.

Figure 5 plots the share of electricity consumption that ASI plants self-generate, as a function of their state's average shortage over the sample period. The upward slope implies that more self-generation is associated with more shortages, as might be expected.

2.7 Self-Generation and Plant Size

Figure 6 illustrates that larger plants are more likely to self-generate. Then, conditional on self-generation, larger plants self-generate a larger share of their electricity. This suggests that there are economies of scale, broadly defined, in both owning and operating generators.

The fact that large plants are more likely to own generators does not mean that they are insulated from electricity shortages. The World Bank Enterprise Survey for 2005 surveyed 2286 manufacturing firms in 50 cities in 16 states about their inputs, outputs, and business environments. As discussed earlier, managers reported electricity supply as the single most important barrier to growth. Table 3 shows that this is true for both small plants (with fewer than 100 workers) and large plants (with more than 100 workers), which will be more likely to appear in the ASI sample. Large plants experience fewer outages. Consistent with the ASI, they are more likely to own generators and, conditional on owning a generator, source a larger share of electricity internally. While small plants report that they lose eight percent of revenues to electricity input disruptions, large plants report losing five percent. Furthermore, 26 percent of large plants report the electricity is the biggest obstacle to growth. Thus, although small plants report being more severely affected by shortages, large plants are significantly affected as well.[5]

Elsewhere Classified (NEC), Matches, and Perfumes and Cosmetics are matched to 'Chemicals', a broader industry where other establishments are more likely to have feedstock for self-generation, and thus a higher self-generation share. Similarly, Natural Gas and LPG Bottling, Coal NEC, and Coke Oven Products are matched to 'Petroleum and Coal Products', another very broad category.

[5]Table A-15 reports simple pairwise correlations from the WBES data. More power cuts are positively associated with firms' reported loss from power cuts, generator ownership, self-generation share conditional on generator ownership, and the probability of reporting that electricity is the biggest obstacle for growth. In the next sections, we formalize what could underlie these cross-sectional comparisons and estimate more precisely the causal effect of electricity shortages on manufacturing productivity and costs.

3 Model

In this section, we develop a model of power shortages. Every day τ, a producer uses capital K, labor L, electricity E, and materials M to produce output Y. Denote a plant i in year t on day τ, yielding daily output $Y_{i,t,\tau}$ and the yearly aggregate $Y_{i,t} \equiv \int_\tau Y_{i,t,\tau} d\tau$. Yearly aggregates will often be the only output that is observable to us in the data, since we do not always observe daily output and input choices.

The daily production function is given by a Cobb-Douglas in capital, labor and materials, and a Leontief in electricity, with a firm productivity Ω:

$$Y = \min\{\Omega K^{\alpha_K} L^{\alpha_L} M^{\alpha_M}, \frac{1}{\lambda} E\} \tag{1}$$

Note that this production function ensures that electricity is used in constant proportion $\frac{1}{\lambda}$ with output. These proportions vary for more and less electricity intensive industries.[6] We assume, as is commonly done, that the Cobb-Douglas component, $\Omega K^{\alpha_K} L^{\alpha_L} M^{\alpha_M}$, has constant returns to scale. This ensures that our problem is homogeneous of degree 1 in (K, L, M, E), and thus $\alpha_K + \alpha_L + \alpha_M = 1$.[7]

3.1 Decision Variables

We assume that inputs fall into three categories: fixed, flexible at the yearly level, and immediately dispatchable.

a) Fixed Inputs

Certain inputs, here capital stock K, will be chosen before the current year. From our perspective, these inputs are fixed.

b) Yearly Flexible Inputs

Other inputs, such as labor, are flexible. However, this flexibility is only true from the perspective of an entire year, since firms cannot hire and fire workers from one day to another. This means that a firm's choices are limited to paths of labor that are constant over the year; i.e., $L_{i,t,\tau} = L_{i,t}$. An alternative interpretation is that these are non-storable inputs, which cannot be stockpiled and used another day.

c) Immediately Dispatchable Inputs

[6] Having Ω inside the Cobb-Douglas aggregator ensures that electricity is Leontief with respect to output rather than with the input bundle.

[7] We have also looked at a production function which is Cobb-Douglas in capital, labor, materials, and electricity. There are two main differences in the predictions of this model. First, plants will always self-produce a small amount of power no matter how high the price of self-generated power is – i.e.; there is no shutdown. Second, higher prices of power look like an input tax on electricity, rather than an output tax as in the Leontief in electricity model. Quantitatively, this makes little difference.

Finally, other inputs are fully flexible– they can be modified from day-to-day. We treat materials and electricity as fully flexible inputs, so $M_{i,t,\tau}$ and $E_{i,t,\tau}$ are daily decision variables.

3.2 Power Outages

Every day, there is a probability δ of having a power outage. In normal times, firms can purchase electricity from the grid at price $p^{E,G}$. However, if there is a power outage, then firms with generators can self-produce electricity, at a price $p^{E,S} > p^{E,G}$. Of course, firms without generators will have zero electricity use on a power outage day, and thus no output on that day.

3.3 Firm's Problem

Firms have the following profit function at the daily level $\Pi_{i,t,\tau}$:

$$\begin{aligned}\Pi_{i,t,\tau} =& p \min\{\Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t,\tau}^{\alpha_M}, \frac{1}{\lambda} E_{i,t,\tau}\} \\ & - p^L L_{i,t} - p^M M_{i,t,\tau} - p^E E_{i,t,\tau},\end{aligned} \tag{2}$$

where p, p^L, p^M are the prices of output, labor, and materials, respectively. Note that capital is excluded, since it is fixed – thus a sunk cost – from the perspective of the yearly decision problem.

Given the Leontief-in-electricity structure of production, cost minimization implies that for any desired level of output Q, the firm produces at a "corner" of the isoquant where:

$$\Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t,\tau}^{\alpha_M} = \frac{1}{\lambda} E_{i,t,\tau}, \tag{3}$$

Given this, one can rewrite the profit function, substituting in for the optimized value of electricity:

$$\Pi_{i,t,\tau} = (1 - \frac{\lambda p^E}{p}) p \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t,\tau}^{\alpha_M} - p^L L_{i,t} - p^M M_{i,t,\tau}. \tag{4}$$

Let $\gamma \equiv \frac{\lambda p^E}{p} = \frac{p^E E}{pY}$, the electricity revenue share. Notice that if $(1 - \gamma) < 0$, then the firm will choose not to produce.

There are three outcomes that can occur, depending on electricity intensity and the relative price of electricity:

a) If $p > \lambda p^{E,S}$, then firms always produces, regardless of power outages.

b) If $\lambda p^{E,S} > p > \lambda p^{E,G}$, then there is no production during power outages, but production otherwise.

c) If $p < \lambda p^{E,G}$, then firms never produces. We can omit the third case: if firms never produce, they never appear in the data.

Notice that firms with higher electricity requirements, i.e. higher λ's, will be more likely to shut down during power outages. Also, firms without generators look like firms that voluntarily choose to shut down in case (b).

The first-order condition with respect to materials yields:

$$\alpha_M(1-\gamma)\frac{pY_{i,t,\tau}}{M_{i,t,\tau}} - p^M = 0. \tag{5}$$

This is the usual first-order condition for materials for a Cobb-Douglas, with the twist that the marginal revenue product of materials is reduced by γ. Since λ is constant, γ is higher when a firm self-generates and pays a price for power of $p^{E,S}$, rather than purchasing from the grid and paying $p^{E,G}$. One can thus interpret $\mathcal{T} \equiv \lambda\frac{p^{E,S}-p^{E,G}}{p}$ as a "tax" on output due to self-generation, and this tax is higher for industries which are more electricity intensive. In other words, the marginal revenue product of materials is given by:

$$MRPM = \begin{cases} \alpha_M(1-\gamma)\frac{pY_{i,t,\tau}}{M_{i,t,\tau}} & \text{if no power outage} \\ \mathcal{T}\alpha_M(1-\gamma)\frac{pY_{i,t,\tau}}{M_{i,t,\tau}} & \text{if power outage} \end{cases} \tag{6}$$

We call this "tax" on output due to shortages the *input cost effect*.

The first-order condition for labor is more complicated, since a firm must integrate over shortage and non-shortage days in their labor decision, so for a firm without a generator or one who will not produce during outages since $\lambda p^{E,S} < p$:

$$MRPL^S = (1-\delta)(1-\gamma)\alpha_L\frac{pY_{i,t,G}}{L_{i,t}} = p^L \tag{7}$$

where $Y_{i,t,G}$ indicates production during non-shortage days, and MRPL is the marginal revenue product of labor for self-generators.

In this case, we get a Cobb-Douglas production function's first-order condition, with the twist that marginal revenue products are reduced by $(1-\gamma)$ *and* $(1-\delta)$, the fraction of the time the plant will be down due to power shortages. This lowered marginal product due to shutdown we call the *shutdown effect*.

If a plant self-generates during power outages, then the first-order condition is given by:

$$MRPL^G = \alpha_L(1-\lambda\frac{p^{E,G}}{p})\left[(1-\delta)\frac{pY_{i,t,G}}{L_{i,t}} + \delta\mathcal{T}\frac{pY_{i,t,S}}{L_{i,t}}\right] = p^L, \tag{8}$$

where $Y_{i,t,S}$ indicates production during shortage periods. This expression includes an "output tax"$\mathcal{T}$ during shortage periods.

3.4 Productivity

3.4.1 Production Function Estimation

We use the first-order condition approach to production function estimation (see the discussion in De Loecker and Warzynski (2012) and Haltiwanger, Bartlesmann and Scarpetta (2013)), to recover production function coefficients α_L, α_M, α_K and λ. As long as plants do not self-generate, which can occur in plants without generators, or in areas without shortages, then γ will be constant at the plant, and is given by the revenue-share of electricity at the annual-level:

$$\gamma = \frac{p^{E,G}E_{i,t,\tau}}{pY_{i,t,\tau}} = \frac{p^{E,G}E_{i,t}}{pY_{i,t}} \tag{9}$$

We can use the first-order condition for labor to get:

$$\alpha_L = \frac{p^L L_{i,t}}{(1-\delta)pY_{i,t,\tau}}\frac{1}{1-\gamma} = \frac{p^L L_{i,t}}{pY_{i,t}}\frac{1}{1-\frac{p^{E,G}E_{i,t}}{pY_{i,t}}}, \tag{10}$$

since $(1-\delta)Y_{i,t,\tau} = Y_{i,t}$. Thus, we can use the familiar equations of α_L to the input revenue share of labor, adjusted by a function of one minus the electricity revenue share.[8]

Likewise, the first-order condition for materials yields:

$$\alpha_M = \frac{p^M M_{i,t,\tau}}{pY_{i,t,\tau}}\frac{1}{1-\gamma} = \frac{p^M M_{i,t}}{pY_{i,t}}\frac{1}{1-\frac{p^{E,G}E_{i,t}}{pY_{i,t}}}, \tag{11}$$

since $M_{i,t,\tau} = (1-\delta)M_{i,t}$, and $Y_{i,t,\tau} = (1-\delta)Y_{i,t}$.

Finally, the capital coefficient is given by $\alpha_K = 1 - \hat{\alpha}_L - \hat{\alpha}_M$, from our constant returns to scale assumption.

We estimate these coefficients by industry, using only plants that do no generate their own power, and use the median of the relevant input share ratio for each industry.

3.4.2 Productivity Effect of Shortages

In an area without power outages, productivity is given by:

$$\omega_{it} = y_{i,t} - \hat{\alpha}_k k_{i,t} - \hat{\alpha}_m m_{i,t} - \hat{\alpha}_l l_{i,t} \tag{12}$$

where lower case variables denote the logarithms of variables in upper case; i.e., $x_{it} = \log(X_{it})$.

If plants have power shortages and choose not to produce, or do not have generators, then their

[8] In a production function Cobb-Douglas in electricity, a similar equation would hold with the absence of an $\frac{1}{1-\gamma}$ correction.

output is given by:

$$\begin{aligned} Y_{it} &= \int_{\tau} \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t,\tau}^{\alpha_M} d\tau \\ &= (1-\delta)^{1-\alpha_M} \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t}^{\alpha_M} \end{aligned} \tag{13}$$

Taking logs, this yields:

$$y_{i,t} = \hat{\alpha}_k k_{i,t} + \hat{\alpha}_m m_{i,t} + \hat{\alpha}_l l_{i,t} + \underbrace{\omega_{i,t} + (1-\alpha_M)\log(1-\delta)}_{\hat{\omega}_{i,t}} \tag{14}$$

and since $1-\delta \leq 1$, $\log(1-\delta) < 0$, so measured productivity $\hat{\omega}_{i,t}$ is decreased. Notice that the $(1-\alpha_m) = \alpha_l + \alpha_k$ term represents the share of inputs that is not storable, in this case, capital and labor.

If plants have generators, and choose to produce, then production is given by:

$$\begin{aligned} Y_{i,t} &= \int_{\tau} \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t,\tau}^{\alpha_M} d\tau \\ &= \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} \left((1-\delta) M_{i,t,G}^{\alpha_M} + \delta M_{i,t,S}^{\alpha_M} \right), \end{aligned} \tag{15}$$

where $M_{i,t,S}$ is the bundle of materials chosen during power outages, and $M_{i,t,G}$ is the bundle of materials chosen otherwise.

Let A represent the loss in output from using different bundles of materials in shortage and non-shortage periods, relative to using the same bundle in both periods.

$$A_{i,t} = \frac{(1-\delta) M_{i,t,G}^{\alpha_M} + \delta M_{i,t,S}^{\alpha_M}}{((1-\delta) M_{i,t,G} + \delta M_{i,t,S})^{\alpha_M}}, \tag{16}$$

where $A < 1$ by Jensen's inequality, since $\left((1-\delta) M_{i,t,G}^{\alpha_M} + \delta M_{i,t,S}^{\alpha_M} \right) < ((1-\delta) M_{i,t,G} + \delta M_{i,t,S})^{\alpha_M}$. For small δ, $A_{i,t}$ is decreasing in δ, and $A_{i,t}$ is increasing in α_M, as $\alpha_M < 1$ and A would be one for a α_M, the linear case.

So we have:

$$\begin{aligned} Y_{i,t} &= \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} \left((1-\delta) M_{i,t,G}^{\alpha_M} + \delta M_{i,t,S}^{\alpha_M} \right) \\ &= A_{i,t} \Omega_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} M_{i,t}^{\alpha_M} \end{aligned} \tag{17}$$

Taking logs, this yields:

$$y_{i,t} = \hat{\alpha}_k k_{i,t} + \hat{\alpha}_m m_{i,t} + \hat{\alpha}_l l_{i,t} + \underbrace{\omega_{i,t} + a_{i,t}}_{\hat{\omega}_{i,t}}, \tag{18}$$

and since $A_{i,t} < 1$, thus $a_{i,t} < 0$, so measured productivity $\hat{\omega}_{i,t}$ is decreased.

Collecting our results, we obtain:

$$\hat{\omega}_{i,t} = \begin{cases} \omega_{i,t} & \text{If no shortages} \\ \omega_{i,t} + (1 - \alpha_M)\log(1 - \delta) & \text{If shortages and no-self generation} \\ \omega_{i,t} + a_{it} & \text{If shortages and self-generation} \end{cases} \tag{19}$$

4 Case Study: Large Textile Manufacturers

Bloom *et al.* (2013) study how improved management practices increased productivity at textile plants in Gujarat, Maharashtra, and Dadra and Nagar Haveli. In the industrial areas where these plants operate, there are scheduled "power holidays" on a given day of the week. In this section, we use data shared by the authors to estimate how these scheduled power holidays affect production.

4.1 Overview and Data

Bloom *et al.* (2013) selected an initial random sample of 66 firms from the set of textile firms that had between 100 and 1,000 employees based in two towns near Mumbai. These 66 firms were contacted and offered free consulting services, and 17 agreed to participate in the consulting program. On average, the firms have 270 employees and sales of $7.5 million per year. The data include 22 plants owned by the 17 firms.

Table 4 presents information on plant locations and scheduled power holidays. The electricity distribution companies spread power holidays throughout the week in order to reduce load on all days, although many of the plants in our sample are in areas with power holidays on Fridays. The plants typically operate continuously: 24 hours a day, every day. Before each power holiday, however, plant managers can choose to shut down for part or all of the day. If they choose not to produce, they can inform workers that they need not come to work. Workers are on 12 hour shifts, and they are paid if and only if they are called in. In the context of our model, labor is thus storable. Similarly, materials such as yarn are storable when the plant does not operate.

Table 5 presents summary statistics. The top panel includes the variables observed at the plant-by-day level. Output is measured in "picks", where one pick is a single rotation of the weaving shuttle. There are two measures of quality: the percent of fabric graded quality level A, and the Quality Defect Index, a severity-weighted measure of the number of defects per meter of fabric. The bottom panel of Table 5 includes variables observed each month. "Shortage" is the Central Electricity Authority's monthly estimated electricity shortage percentage for the state where the plant is located.[9] Diesel prices are the Mumbai prices recorded by the website mypetrolprice.com.

[9]Throughout the paper, we use the word state to refer to both states and Union Territories. (Dadra and Nagar Haveli is a Union Territory, not a state.)

In this section, all rupees are deflated to constant 2004-2005 values using the textile wholesale price index (Office of the Economic Advisor 2013).

Figure 7 presents the distributions of output at an example plant for each of the seven days of the week. The dashed line is output on Fridays, when the plant has power holidays, while the solid lines represent output on each of the other six days. The distributions are very similar on non-holidays, with a mode of about 12,000 picks per day. On most power holidays, output appears to be unaffected. On some power holidays, output is roughly half, suggesting that the plant cancels one 12-hour shift, and output drops to zero on a small number of power holidays. This figure illustrates the clear relationship between power holidays and output.

4.2 Empirical Estimates

4.2.1 Effects on Output

We now estimate the effects of power holidays on output. Denote $Y_{i\tau}$ as production at plant i on day τ. $\widetilde{Y}_{i\tau}$ is production normalized by plant i's sample average production: $\widetilde{Y}_{i\tau} = Y_{i\tau}/\overline{Y}_i$.[10] The variable ϕ_i is a vector of 22 plant indicators, while θ_τ represents 1339 day-of-sample indicators. The estimating equation is:

$$\widetilde{Y}_{i\tau} = \rho \cdot 1(\text{Power Holiday}_{i\tau}) + \phi_i + \theta_\tau + \varepsilon_{i\tau} \tag{20}$$

Table 6 presents the results of this regression, with standard errors clustered by plant. Column 1 presents the above specification, except without the day-of-sample controls θ_τ. Column 2 is the exact specification above. These columns show that average production is 7.4 to 9.7 percent lower on power holidays.

According to the consulting team that worked with the factories, there is typically no grid electricity available for the 24 hours of the scheduled power holiday. However, there are both "type I" and "type II" classification errors. During the winter months when electricity demand is lower, there may be unscheduled power availability during scheduled power holidays. During all months, especially the summer months when electricity demand is higher, there can also be unscheduled power cuts on any day.

Column 3 measures this by estimating how production on power holidays and non-holidays varies with the monthly CEA shortage estimate. On non-power holidays, output is not statistically significantly associated with shortages. This is consistent with the fact that when power cuts occur on non-power holidays, plants typically self-generate instead of shutting down. One reason why plants would shut down on pre-scheduled power holidays but not shut down during power cuts on

[10] We normalize because production varies substantially within and between the different plants, and we do not want the coefficient estimates to be driven by outliers. This normalization is preferable to using $\ln(Y_{i\tau})$ or $\ln(Y_{i\tau}+1)$ as the dependent variable because $Y_{i\tau} = 0$ on some days, and this large variation makes it incorrect to interpret the coefficients as approximately reflecting percent changes in Y.

power holidays is that the advance notice of pre-scheduled power holidays changes labor from being non-storable to storable.

The coefficient on 1(Power Holiday), which represents the intercept when the CEA estimates zero shortages, is statistically zero. Output on power holidays decreases by 0.6 percentage points as shortages increase by 1 percentage point. This suggests that the managers have some ability to predict when there will be more electricity on a scheduled power holiday, and on these days they call in workers and produce with some combination of purchased and generated electricity. These results highlight that the effect of scheduled power holidays on output depends on the severity of the underlying shortage that the holidays are designed to address. If there are in fact no shortages, then the distribution company will supply power on scheduled power holidays, and firms appear to be able to predict this. Column 4 includes power holiday-by-month controls, to control for any time-varying factors such as demand or diesel prices. This does not change the results relative to column 3.[11]

4.2.2 Effects on Energy Costs

We now estimate the input cost effect: the increase in electricity costs when power holidays force a switch from grid electricity to self-generated electricity. We observe total energy costs - electricity plus generator fuel - at the monthly level. After conditioning on total monthly production, the relationship between energy costs and the share of production on power holidays tells us the incremental marginal cost of self-generated electricity.

Let G_{im} represent the share of output produced on power holidays. We denote $\widetilde{E}_{im}$ and $\widetilde{Y}_{im}$ as plant i's energy costs and output for month m, normalized by each plant's average monthly values. Analogous to above, ϕ_i is a plant fixed effect, and θ_m is a full set of month-of-sample dummies. The variable S_{im} reflects the estimated electricity shortage in plant i's state in month m. The regression is:

$$\widetilde{E}_{im} = \beta_1 G_{im} + \beta_2 S_{im} + \beta_3 \widetilde{Y}_{im} + \phi_i + \theta_m + \varepsilon_{im} \tag{21}$$

Table 7 presents the results, again with standard errors clustered by plant. Columns 1-3 exclude the month-of-sample indicators θ_m and progressively add controls for diesel prices and shortages, and Column 5 is exactly Equation (21). The estimated $\widehat{\beta}_1$ imply that shifting 100 percent of production from non-power holidays to power holidays would increase monthly energy costs by 61 to 81 percent. For comparison, the World Bank Enterprise Survey data in Table 3 suggest that grid electricity costs Rs 4.5 per kilowatt-hour, while generator electricity costs Rs 7 per kilowatt-hour, or 56 percent more.

[11] Our model does not capture potential effects of electricity shortages on output quality, and so we would understate productivity losses if shortages affect output quality along with quantity. We have tested this, finding no statistical difference in either measure of output quality on power holidays vs. non-power holidays.

4.3 Estimating Productivity Losses

We can now combine the model with empirical estimates to assess the input cost and shutdown effects of scheduled power holidays on our sample of textile plants. We make several modifications to the model in Section 3 in order to carry out this calculation. First, we assume that at a given time on a power holiday, a plant has either shut down completely or is operating at the typical production rate for a non-power holiday. We do this because it is not clear how to separately identify production lost due to complete shutdown vs. the production lost due to decreased rate of production due to higher energy costs. Second, we assume that both labor and materials are fully storable during shutdowns.

Table 8 presents results. The top panel calculates the input cost effect. This is the proportion of electricity that is self-generated, which we assume to be equal to the share of production on power-holidays (G), multiplied by the percentage increase in electricity costs when self-generating ($\widehat{\beta}_1$) and by the electricity input cost share. Power holidays increase input costs by 0.32 percent of total revenues. Intuitively, this effect is so small both because the electricity input cost share is small and because only one-tenth of production is on power holidays.

The bottom panels calculate output loss and the shutdown effect on measured TFP. We estimate that power holidays reduce output by 1.1 percent, the product of 1/7 days that are power holidays and an estimated 7.4 percent output reduction on those days. The shutdown effect is the loss of non-storable inputs during the 1.1 percent of the time that plants are shut down. From Section 3, the change in log TFP is $\alpha_K \cdot \log(1-\delta)$, where δ is the percent of time shut down. The non-storable input is capital, and the production function coefficient α_K applies the approach in Section 3 to ASI data on all plants in India classified with the same 1987 NIC code (235). The table shows that power holidays reduce TFP by 0.21 percent.

These textile plants are "discrete" industries: if production stops due to a power cut, production can restart later with essentially no loss. The storability of materials, and of labor when power cuts are scheduled, reduces the TFP effect in this industry. By contrast, "process" industries, in which materials go bad during shortages, could have either larger TFP effects or larger input cost effects. Furthermore, all of these plants have generators, while many Indian manufacturers do not. To learn more about the broader Indian manufacturing sector, we now to turn to data from the Annual Survey of Industries.

5 Nationwide Analysis

This section presents estimates of the effects of electricity shortages on manufacturing plants nationwide. In four subsections, we detail the estimation strategy, instruments and first stages, empirical results, and per unit cost effects.

5.1 Data

We use India's Annual Survey of Industries (ASI) for 1992 through 2007. The survey is split into two schemes: the census scheme and the sample scheme. In each year, the census scheme surveys all manufacturing establishments with over 100 workers, while the sample scheme surveys a rotating sample of one-third of establishments below that size.[12] Since 1998, the publicly-available version of the ASI includes establishment identifiers that are consistent across years. We also have an earlier version of ASI data that was acquired in India and is not publicly available, which contains consistent establishment identifiers for years before 1998. Combining these two datasets gives us an establishment-level panel for our entire sample.

The ASI is comparable to manufacturing surveys in the United States and other countries. It comprises several modules, covering value of fixed capital stock and inventories, loans and cash flow information, cost and quantities of labor, materials, fuels, and other inputs, value of output, and other occasional questions. The reporting period is the Indian fiscal year, which is April 1 through March 31; when we refer to a survey year, we refer to the calendar year at the beginning of the fiscal year. All financial amounts are deflated to constant 2004 Rupees. Appendix A gives more detail on the ASI data preparation and cleaning.

Table 9 gives descriptive statistics for the full ASI dataset. There are approximately 517,000 establishment-by-year observations. The average establishment employs a median of 33 people and has median gross revenues of 18 million Rupees. One of the benefits of the ASI over similar datasets in India and other countries is that we observe the physical quantity of each establishment's total electricity purchases and self-generation in each year. The sum of these two variables, minus reported sales of electricity, yields Electricity Consumed. Self-generation share is defined as Electricity Self-Generated divided by Electricity Consumed.

Table 2 presents other state-level data that we combine with the ASI. Aside from the electricity market variables discussed earlier, we also use weather and temperature data from the National Climactic Data Center's Global Summary of the Day. These data provide average daily temperatures in Fahrenheit at over 100 weather stations in 25 different states. The change in average cooling degrees for state s in year y, denoted ΔC_{sy}, is the mean of the changes across all stations in the state. This is a strong correlate of changes in electricity demand for air conditioning.[13]

[12] The sampling rules have changed somewhat over time. The census sector, from which 100 percent of factories are sampled, was factories with 50 or more workers (100 or more if without electric power) until 1986-1987, 100 or more workers between that year and 1996-1997, 200 or more workers from then until 2003-2004, and then 100 or more workers since then. One-fifth of smaller factories were sampled since 2004-2005. The selection was done as a rotating panel such that plants are surveyed exactly once every third (or fifth) year, subject to constraints that sufficient numbers of factories had to be sampled to assure representativeness at the state and industry level (MOSPI 2009).

[13] We tested alternative base levels for calculating cooling degree-days ranging from 55 to 80, finding the standard 65 degree base to be most predictive of annual electricity demand conditional on state and year fixed effects. Since making this determination, we have not experimented further with alternative constructions of the cooling degree-days variable.

5.2 Estimation Strategy

Define Y_{ijsy} as output at plant i in industry j in state s in year y. In different regressions, the left-hand-side variable could alternatively be self-generation share, fuel input cost share, or productivity. Define S_{sy} as the electricity shortage in state s in year y, ranging from zero to one. The variables μ_{jy}, λ_s, and θ_y are vectors of indicators for two-digit industry-by-year, state, and year, respectively. Because errors are serially correlated, the first difference estimator is more efficient than fixed effects.[14] Denoting Δ as the annual difference operator, the estimating equation is:

$$\Delta \ln Y_{ijsy} = \tau \Delta S_{sy} + \mu_{jy} + \theta_y + \lambda_s + \varepsilon_{ijsy} \tag{22}$$

Standard errors are robust and clustered by state and year. Although the ASI sample scheme plants have sampling weights, we weight all observations equally. This increases power, and because the difference estimator drops establishments not observed in consecutive years our estimates are already not representative of the entire manufacturing sector. In the simulations in section 6, we do use the sampling weights to construct nationally-representative estimates.

5.3 Instruments and First Stages

Shortages could be econometrically endogenous to some outcomes, in particular output and productivity. There could be reverse causality: increases in manufacturing productivity within a state and year could cause plants to demand more electricity in order to produce more output, and this increase in electricity demand could directly cause shortages. There could also be omitted variables bias: general improvements in economic conditions within a state could increase both industrial output and growth in other sectors, which could cause shortages. Furthermore, shortages could also be measured with error, causing attenuation bias.

To address these concerns, we experiment with two instruments for ΔS_{sy}. The first instrument, denoted ΔH_{sy}, is derived from hydroelectricity production, which varies from year to year due to reservoir inflows. The variable H_{sy} is the predicted share of state consumption that can be fulfilled by hydroelectric generation in state s in year y. As there are positive shocks to reservoir inflows, and thus to hydroelectricity generation, a larger share of state consumption can be fulfilled, and shortages should decrease. Intuitively, the denominator should be total electricity consumption in state s in year y, but this is determined partially by the extent of shortages. Thus, the denominator is national electricity consumption multiplied by the average ratio of state to national consumption for all years of the sample:

$$H_{sy} = \frac{\text{Hydro Electricity Production}_{sy} \text{ (GWh)}}{\left[\begin{array}{c}\text{National Electricity} \\ \text{Consumption}_y \text{ (GWh)}\end{array}\right] \cdot \left[\begin{array}{c}\text{Average Ratio of State} \\ \text{to National Consumption}_s\end{array}\right]} \tag{23}$$

[14] tk See [FILL IN] for a discussion of this issue.

Figure A-10 illustrates the cross-state variation in the importance of hydroelectricity. Andra Pradesh, Himachal Pradesh, Karnataka, Kerala, Orissa, and Uttaranchal are especially reliant on hydroelectricity. Figure A-9 shows the time path of hydroelectricity production for these states. In essence, the instrument is the product of Figure A-10 and Figure A-9.

The identifying assumption is that changes in hydroelectricity production are associated with changes in industrial production only through their effects on electricity shortages. The exclusion restriction would be violated if economic growth caused increases in industrial output and electricity demand, and electricity suppliers respond in equilibrium by producing more. However, the marginal cost of hydroelectricity production is relatively low, and annual production is constrained by the amount of water available behind reservoirs. In contrast, the exclusion restriction would be violated for production technologies such as coal power plants that have higher marginal costs, because their output is determined in equilibrium with demand.[15] In the state-by-year panel, ΔH is not statistically signficantly associated with changes in the CEA's estimated electricity requirement. The fact that hydro production is not associated with demand strongly supports the exclusion restriction.

The second instrument is the change in average cooling degrees, denoted ΔC_{sy}, which parallels the instrument used in previous work by Fisher-Vanden, Mansur, and Wang (2012). Figure A-11 illustrates the annual levels of annual cooling degrees in six example states. The identifying assumption is that changes in temperatures are associated with changes in industrial production only through their effects on electricity shortages.

Table 10 presents the first stages. The cluster and heteroskedasticity-robust F-statistic on the excluded instruments when using both instruments in the third column is 4.99, while the F-statistic for the hydro instrument alone is 8.70. This means that the cooling degrees instrument is currently not providing much power. This may change in future drafts as we integrate better temperature data, which is being procured from officials in India. For this draft, we thus estimate our IV regressions instrumenting only with ΔH. This 8.70 F-statistic is approximately equal to the Stock and Yogo (2005) critical value for 15% bias of the IV estimates, which is 8.96. Thus we are moderately concerned about bias from weak instruments.

5.4 Regression Results

Table 11 presents results of Equation (22) for four different outcomes: self-generation share, natural log of fuel input cost share, natural log of output, and natural log TFP, respectively. The top and bottom panels present OLS and instrumental variables results, respectively. In the OLS results in the top panel, a one percentage point increase in shortages is associated with about a 0.2 percentage

[15] To substantiate this, we gathered data from the CEA on inflows into 22 large reservoirs. We regressed inflows on annual hydroelectricity production, finding an R^2 of 0.87. While the R^2 should not be 1 because the data include reservoirs that supply only 40 percent of India's hydroelectric generating capacity, the very high R^2 indicates how inflows, not demand, determine hydroelectric production. Note that it is not possible to directly use inflows as our instrument because only 2/5 of states that have positive hydro generation have reservoirs in the inflows data.

point increase in self-generation share and a 0.94 percent increase in fuel input cost share. The IV point estimates are approximately three times larger. While they are imprecisely estimated, this difference suggests that the IV helps to address measurement error in the Shortage variable. When examining these two outcome variables, we limit to the smaller sample of establishments that report producing electricity in at least one year. Non-producer establishments mechanically have no elasticity of self-generation with respect to shortages. Their fuel input cost share also is statistically unassociated with shortages, as one would expect.

The IV point estimates suggest that a one percentage point increase in shortages reduce output and TFP by about 0.8 percent. These are imprecisely estimated, however, and the confidence intervals include a range of possible effect sizes. The OLS estimates are less negative than the IV estimates, which suggests that omitted variables such as improved economic conditions could be positively associated with both shortages and output.[16] [17]

5.5 Quantifying the Input Cost Effect

Table 12 uses the coefficients from Table 11 to quantify the effects of shortages on input costs. The first panel is based on the IV estimate that a one percentage point increase in shortages causes a 0.78 percentage point increase in self-generation share. Using the 2.5 Rs/kWh difference in marginal electricity costs for grid vs. self generated electricity reported in the World Bank Enterprise Survey and the mean electricity intensity across industries, this translates to a 0.20 percent unit cost increase.

The results using the fuel input cost share coefficient need not be the same: for example, manufacturing establishments such as pulp plants and sugar cane mills can burn wood or bagasse to produce electricity, so an increase in self-generation would not be associated with an increase in fuel purchases. The second panel assumes that a one percentage point increase in shortages increases fuel input cost share by one percent. The mean fuel input cost share across all plants is 0.054, and so the short-run effect of the shortages is to increase fuel input costs by 0.42 percent.

If both grid electricity and generator fuels were priced at social marginal cost, this would represent a social welfare loss. As discussed earlier, however, industrial electricity prices are set

[16] Table A-16 splits the sample into generators and non-generators and repeats the estimates of Equation (22) for output and TFP. In this draft, the coefficients are imprecisely estimated, and not significantly different from each other, or zero, at even the 10% level. However, the point estimates suggest that both productivity and output drop more for non-generators during shortages.

[17] Table A-17 repeats the IV estimates but includes the interaction of shortages with the establishment's median log output. The instruments are ΔH and the interaction of ΔH and median log output. Column 1 shows that larger plants increase self-generation more than smaller plants during shortages. Consistent with this, column 2 suggests that larger plants increase fuel use more, although the point estimates are not statistically significant. Again, columns 1 and 2 are limited to the sample of plants that do self-generate, so these results are not simply because larger plants are more likely to have generators. This result is also different than the stylized fact in Section 2 that conditional on owning generators, larger plants self-generate slightly more, as that could be driven by factors that make self-generation more profitable regardless of the shortage level. Instead, the result in Table 14 suggests that larger plants are better able to respond to shortages through self-generation. It suggests that larger plants should have smaller output and productivity losses during shortages, although the results for these outcomes in columns 3 and 4 are not statistically significant.

artificially high to cross-subsidize other consumer categories, and there are also various forms of subsidies and distortions in fuel markets. Thus, these numbers should be interpreted as cost shocks to industry, not necessarily a social welfare loss.

6 Simulations

In this section we quantify the welfare loss from missing power supply. We use the structure provided by our model for this exercise, but need additional information from the ASI to identify parameters in the model.

6.1 Calibrated Parameters

Table 13 presents the parameters that we use to calibrate the predictions of the model. We use the ASI data presented in section 5.1 as the universe of plants for which make a prediction. We apply the approach described in section 3.4 to recover plant-level production function coefficient α_l, α_k, and α_m from the input cost shares of non-self generators according to equations (10) and (11), and estimate γ using the electricity cost share for plants that do not generate any power themselves (non generators). The data on the fraction of the year in which there are shortages δ comes from our own collection efforts described in section 2.1.

Finally, we need to make an assumption on the relative cost of electric power bought from the electric grid ($p^{E,G}$), versus power that is self-generated ($p^{E,S}$). We use the responses to the World Bank Enterprise Survey to the question on the cost of grid power versus self-generated power presented previously in Table 3. Only the ratio between these two price matters, and we assume that self-generated power is 55% more expensive than grid power.

6.2 Welfare Predictions

To get a handle on the effect of power shortages on welfare, we compute the loss in output and measured TFP from these shortages. Specifically, we compute the predicted output under the observed shortages, and compare these to the case without any shortages; i.e., $\delta = 0$.

Table 14 presents results from this exercise for 2005, but these prediction are fairly similar across any year from 1992 to 2007. First, in 2005, there are, on average, shortages 7.2% of the time. We predict a loss in output of 6.5% from these shortages. However, this loss in output is starkly different for plants who have a generator versus plants that do not. Plants with a generator suffer an output loss of only 0.9%. To understand this small effect, remember that electricity purchases are only 2.5% of revenues. Thus for plants with a generator, a power outage is equivalent to 55% increase in the price of power, or a 1.7% increase in costs the 7.2% of the year shortages occur. This small increase in costs during power outages rationalize the slight effect of shortages on output that we found in section 4 for large textile producers, all of which have backup generators.

However, for non-generators, output would fall by 9.7%. Notice that this is even greater than the 7.2% of the time where the plant cannot operate due to shortages. The effect of shortages on output is amplified because of the non-storability of labor. Anticipating a power outage, firms hire less labor than they would otherwise, and this enhances the effect of shortages. Given the large losses for plants without generators, this begs the question of why these plants do not purchase generators in the first place, which we turn to in section 6.4.

Second, we shows the predicted losses in measured TFP due to shortages. Echoing the stark contrast between generators and non-generators we found for output, the loss in TFP is almost zero for plants that self-generate, versus a 2.4% TFP loss for Non-Generators. Thus, the average predicted TFP loss is only 1.2%.

6.2.1 Robustness

A natural question has to do with the robustness to alternate assumptions in our model and the plausibility of the model's predictions.

There are few papers that look at the elasticity of output with respect to power shortages. Most prominently, Davis, Grimes and Haltiwanger (2008) investigate the elasticity of output with respect to the price of electricity in the United States. Since a power outage is – for generators – equivalent to an increase in the price of electricity, we can compare the elasticity of output with respect to price of power in our model to the one estimated in Davis, Grimes and Haltiwanger (2008). We compute an elasticity of output with respect to the price of electricity of -0.4, while Davis, Grimes and Haltiwanger (2008) find an elasticity of -0.6. So our model, if anything, under predicts the response of output to shortages for generators, but not by a large amount.

Second, we look at changing the assumption on the elasticity of demand faced by firms. In the model we described, we assume that the sales generating production function had constant returns to scale. An alternative assumption is to think of the sales generating production function as a combination of a constant returns to scale production function with a constant elasticity demand curve, with an elasticity of say $\epsilon = -4$.[18] Using this assumption, we get a weighed loss of 2.5% using a different elasticity of demand, mainly because self-generators reduce their output by 0.4% rather than 0.9%.

Third, we used data from the World Bank to motivate the assumption that self-generated power is 55% more expensive than grid generated power. Suppose instead that self-generated power is *four* times more expensive as grid supplied power. We find a weighted loss of 12.8% instead of 7.2%, in large part because plants who generate reduce their output by a little more than 2.1%.

Fourth, we should stress that the results are sensitive to the measurement of generators versus

[18] See Foster, Haltiwanger, Syverson (2008), Bloom (2009), and Asker, Collard-Wexler, and De Loecker (2013) for discussions on these topics. Consider the production function for physical output given by a Cobb-Douglas: $Q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}$, and a constant elasticity of demand curve $Q_{it} = B_{it} P_{it}^{-\epsilon}$. Combining these two equations, we obtain an expression for the sales-generating production function $S_{it} = \Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}$ where $\Omega_{it} = A_{it}^{1-\frac{1}{\epsilon}} B_{it}^{\frac{1}{\epsilon}} b$, and $\beta_X = \alpha_X(1 - \frac{1}{\epsilon})$ such that $X \in \{K, L, M\}$.

non-generators. We find that almost half of plants in the ASI report producing no power whatsoever, and even for plants with over 500 employees, approximately 30% report no generation. If we overstate the fraction of plants that are non-generators, our welfare effects will also be overstated. However, the World Bank Enterprise Survey explicitly asks plants if they own a generator, and we find a similar fraction of firms are flagged as owning generators in the ASI and in the World Bank data.

6.3 Firm Size Distribution

An important question is the extent to which the shortages affect firms differently. In particular, the lack of electrical infrastructure has been discussed to have disproportionate effects on smaller firms, since these small firms have more difficulty in replicating their own infrastructure. Tybout (2000) discusses several potential causes for why the firm size distribution in developing countries tends to have a "missing middle". Hsieh and Klenow (2012) propose that electricity shortages combined with economies of scale in self-generation could be an important factor benefitting large establishments.

Figure 8 shows the change in the rate of return on capital due to eliminating shortages. Specifically, this figure shows the median change in the rate of return for firms with different capital stocks. Strikingly, small firms would benefit the most from eliminating shortages, with an implied increase in their rate of return of over 10% for firms with less than 0.5 million rupees of assets, versus less than 2% for firms with over 9 million rupees of assets. Small firms are disproportionately affected by shortages because they tend not to have generators, and thus have larger losses in output due to shortages.

6.4 Decision to Purchase a Generator

Most of the loss in output is due to plants who do not have a generator. This begs the question of why some plants choose not to buy generators. To get at this issue, we compute the cost of a generator at which a plant would break even from purchasing it.

More precisely, we first compute the increase in profits that would occur if a firm purchased a generator.[19] We find that profits would increase by an average 8 percent upon the purchase of a generator – excluding the cost of the generator itself, of course. We find a median of 425 Rupees per KW of generating capacity as a break-even cost of a generator.[20] This is a remarkably small expense, and we might expect a generator to pay for itself in under three months. Given that a diesel generator lasts about 10 years operating full time during shortages, the fact that firms choose not to purchase backup capacity is puzzling.

[19] Profits are computed using equation (4) along with the optimized values for labor and materials.

[20] The median plant would require about 250 KW of generation capacity, assuming a plant purchases the ability to fully back up it's power requirements.

7 Conclusion

India has experienced a large-scale failure to provide electricity to its manufacturing sector. This paper has focused on assessing the effects of these power shortages on the manufacturing sector, both in terms of output and productivity.

Using a production function model calibrated to data from the Annual Survey of Industries, we predict output losses of 6.5 percent and productivity losses of 1.2 percent due to power shortages. However, these losses are much smaller for plants with backup generating capacity, with output losses on the order of 0.9% and virtually no loss in TFP. Since electricity is a small share of input costs, and generator produced electricity is reasonably cheap, plants with generators should almost completely replace grid power with generated power during shortages.

For a small sample of textile plants for which we have extremely detailed data, we find very small losses in output due to power shortages, on the order of 0.9 percent. But these textile plants all have extensive backup generators, so this small effect is precisely the prediction from our model.

Next, we examine the entire Indian manufacturing sector using data from the ASI. Here we find larger effects of shortages on output, on the order of 8 percent. However, these effects are not precisely estimated, in large part because we need to find instruments for shortages, since fast growth in output and productivity at manufacturing plants could, by itself, cause these shortages in the first place.

Overall, this paper presents a nuanced view of power outages. These outages can have reasonably large negative effects on output, on the order of 6-8 percent. However, in understanding the large differences in TFP between a developing country like India, and the United States, electric shortages do not appear to play a large role.

The main limitations of this study have to do with the focus on the short-run effects of shortages, which hold the capital stock and location of plants fixed. With these data, we cannot say more about other potential effects, such as wear and tear on machinery. We also cannot say more about effects on the entry and exit margin, although if the effects on TFP and input costs are small, this suggests that the entry and exit effects would also be small. Moreover, there is much scope for getting better data on how firms respond to shortages, particularly at less sophisticated and smaller scale operations.

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Tables and Figures

Table 1: Biggest Obstacle for Growth

Problem	**Percent**
Electricity	33
High Taxes	16
Corruption	10
Tax Administration	8
Cost of and Access to Financing	6
Labor Regulations and Business Licensing	5
Skills and Education of Available Workers	4
Access to Land	3
Customs and Trade Regulations	2
Other	12

Notes: Data are from the 2005 World Bank Enterprise Survey. Responses to question, "Which of the elements of the business environment included in the list, if any, currently represents the biggest obstacle faced by this establishment?"

Table 2: State-Level Data Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
Requirement (TWh)	18.4	23	0.024	141	616
Availability (TWh)	16.8	20.5	0.024	118	616
Shortage	0.073	0.077	0	0.48	616
Peak Demand (MW)	3091	3690	6	21,069	616
Peak Met (MW)	2665	3094	6	16,417	616
Peak Shortage	0.11	0.10	0	0.5	616
Reservoir Inflows (Billion Cubic Meters)	16.9	22.3	0	116	169
Hydro Generation (GWh)	4330	13.8	0	120,387	682
Total Electricity Sold (TWh)	21.3	14.1	1.68	72.8	234
Change in Average Cooling Degrees	0.011	0.18	-0.76	1.04	766
Rainfall (meters)	12.5	7.05	2.38	37	628
GDP (Billion 2004 Rupees)	513	571	7	2869	921

This table presents descriptive statistics for data that vary at the state-by-year level. Average cooling degrees for a given weather station and year is $\sum_{\text{Days in Year}} \max(0,\text{Daily Average Temperature}-65)/365$.

Table 3: Small and Large Plants in 2005 WBES

Plant Descriptions	Small Plants	Large Plants
Number of Plants Surveyed	1719	306
Number of Workers (Mean)	23	494
Gross sales, in million Rupees (Median)	5.7	172
Electricity Shortage Questions		
How [many times in 2005] did your establishment experience power outages or surges? (Mean)	132	99
Does your establishment own or share a generator? (Percent)	46	83
What percent of your electricity comes from the generator? (Mean)	10	17
What is the average cost [in Rs/kWh] for generator electricity? (Median)	7	7
What is the average cost [in Rs/kWh] for public grid electricity? (Median)	4.5	4.5
What were your percentage losses from power outages or surges? (Mean)	8.0	4.9
Electricity is the "biggest obstacle for operation/growth" (Percent)	34	26

Notes: Data are from the 2005 World Bank Enterprise Survey. "Small Plants" have less than 100 workers, while "Large Plants" have 100 or more workers.

Table 4: Scheduled Power Holidays

Number of Plants	State	Scheduled Power Holidays
1	Gujarat	Saturday before Sept 26, 2008; Sunday between Sept 26, 2008 and July 10, 2009; Monday after July 10, 2009
1	Dadra and Nagar Haveli	Sunday
1	Gujarat	Saturday before July 10, 2009; Sunday after July 10, 2009
1	Maharashtra	Tuesday
1	Maharashtra	None
3	Gujarat	Saturday before July 10, 2009; Monday after July 10, 2009
14	Maharashtra	Friday

Table 5: Textile Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Daily Data					
Production (1000s of picks)	442	1455	0	9098	26,114
Percent Grade A	55.3	28.5	0	100	12,489
Quality Defect Index	4.02	5	0.13	56.6	13,223
1(Planned Power Cut)	0.14	0.34	0	1	46,288
Monthly Data					
Energy Costs (Rs 1000s)	300	281	8.9	1466	307
Labor (1000s of Hours)	32.3	20.7	4.4	148.2	575
Power Holiday Output Share	0.11	0.05	0	0.33	902
Diesel Price (Rs/liter)	35.0	1.6	31.4	38.3	902
Shortage	14.5	7.5	0	25.7	902

Table 6: Output and Quality on Planned Power Holidays

	(1)	(2)	(3)	(4)	(5)	(6)
	Output	Output	Output	Output	Defect Index	Percent Grade A
1(Power Holiday)	-0.097	-0.074	-0.006	0.025	0.009	-0.338
	(0.025)***	(0.017)***	(0.022)	(0.027)	(0.017)	(0.254)
1(Power Holiday) x Shortage			-0.006	-0.006		
			(0.003)**	(0.003)**		
Shortage			0.001	0.001		
			(0.004)	(0.004)		
N	26,114	26,114	26,114	26,114	13,223	12,489
Day-Specific Controls	No	Yes	Yes	Yes	Yes	Yes
Power Holiday x Month Controls	No	No	No	Yes	No	No

Notes: tk This presents estimates of Equation (20). The outcome variable for columns 1-4 is $\widetilde{Y}_{i\tau}$, plant i's production on day τ, normalized by plant i's average daily production. Columns 3 and 4 limit the sample to power cut days only. The outcome variables for columns 5 and 6 are the natural log of the Quality Defect Index and the percent of output that is quality level A. Standard errors clustered by plant. *,**, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively.

Table 7: Monthly Energy Cost Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy	Energy	Energy	Energy	Energy	Labor
Power Holiday Output Share	0.610	0.727	0.685	0.791	0.811	
	(0.362)	(0.367)*	(0.378)*	(0.314)**	(0.343)**	
Diesel Price (Rs/liter)		0.023	0.026			
		(0.013)	(0.013)*			
Shortage			-0.006		-0.003	
			(0.005)		(0.005)	
Normalized Output					0.232	
					(0.167)	
Normalized Output on Power Holidays						0.552
						(0.273)*
Normalized Output on Non-Power Holidays						0.148
						(0.138)
N	307	307	307	307	307	575
Month-by-Year Controls	No	No	No	Yes	Yes	Yes

Notes: This presents estimates of Equation (21). The outcome variable for columns 1-5 is $\widetilde{E}_{im}$, plant i's total energy cost in month m, normalized by plant i's average monthly energy cost. The outcome variable for column 6 is $\widetilde{L}_{im}$, plant i's labor hour input in month m, normalized by plant i's average monthly labor hours. Standard errors clustered by plant. *,**, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively.

Table 8: Losses on Planned Power Holidays

Input Cost Effect	
Share of production on power holidays (G)	0.11
Increase in energy costs ($\widehat{\beta}_1$)	0.77
Mean electricity input cost share	0.038
Input Cost Effect (%)	0.0032
Output Loss	
Share of days that are power holidays	1/7
Output loss on power holidays ($\widehat{\rho}$)	0.074
Annual output loss (δ)	0.011
Shutdown Effect on Measured TFP	
Share of non-storable inputs (α_K)	0.2
Shutdown Effect (%): $\alpha_K ln(1-\delta\rho)$	-0.0021

Table 9: Annual Survey of Industries Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Revenues (million Rupees)	292	3765	0*	781,964	517,463
Total Persons Engaged	161	751	0	61,869	517,275
Materials Purchased (million Rupees)	175	2741	0	636,466	517,355
Fuels Purchased (million Rupees)	12	154	0	21,178	395,403
Electricity Purchased (million Rupees)	8.8	84.1	0	9935	383,998
Electricity Consumed (GWh)	3.07	45.1	0*	6693	499,055
Electricity Purchased (GWh)	1.97	29.4	0	6184	499,699
Electricity Self-Generated (GWh)	1.11	29.5	0	6671	498,556
Electric Intensity (kWh/Rs)	0.013	0.020	0*	0.39	499,054
Self-Generation Share	0.085	0.20	0	1	498,556
Fuel Input Cost Share	0.054	0.12	0	3.7	395,403

This table presents descriptive statistics for data from the Annual Survey of Industries.

Table 10: First Stages

	(1)	(2)	(3)
	Hydro	CDD	Both
D.Hydro_Inst	-0.066		-0.068
	(0.022)***		(0.022)***
Change in CDD		0.005	0.005
		(0.003)*	(0.003)
N	185,374	168,825	185,374
First Stage F-Stat	8.69	2.58	4.99

Notes:

Table 11: Average Effects of Shortages

Panel A: OLS

	(1)	(2)	(3)	(4)
	Self-Gen Share	Fuel Input Cost Share	ln(Y)	ln(TFP)
D.Shortage	0.206	0.939	-0.069	0.023
	(0.050)***	(0.211)***	(0.064)	(0.057)
N	96,025	96,801	184,033	180,947

Panel B: IV

	(1)	(2)	(3)	(4)
	Self-Gen Share	Fuel Input Cost Share	ln(Y)	ln(TFP)
D.Shortage	0.779	2.525	-0.843	-0.820
	(0.336)**	(2.002)	(0.507)*	(0.467)*
N	96,738	97,580	184,961	181,880

Notes: This table presents estimates of Equation (22). The top and bottom panels present OLS and instrumental variables results, respectively. Standard errors clustered by state and year. *,**, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively.

Table 12: Input Cost Effect from ASI

Based on Self-Generation Share	
Effect of Shortages on Self-Gen Share ($\widehat{\tau}$)	0.78
Average Shortage	0.078
Increase in Self-Generation Share	0.061
Electric Intensity λ (kWh/Rs)	0.013
Per unit electricity price increase $p^{E,S} - p^{E,G}$ (Rs/kWh)	2.5
Percent total cost increase	0.0020
Based on Fuel Input Cost Share	
Effect of Shortages on Fuel Input Cost Share ($\widehat{\tau}$)	1.0
Average Shortage	0.078
Mean Fuel Input Cost Share	0.054
Increase in Fuel Input Cost Share	0.0042
Percent total cost increase	0.0042

Notes: tk.

Table 13: Calibration Parameters

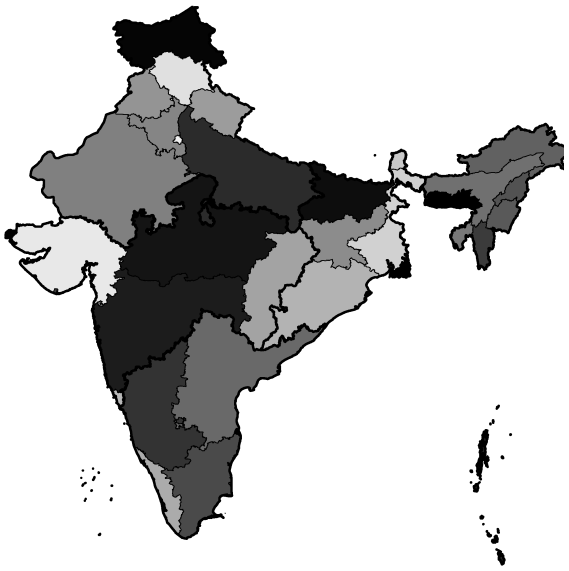
Parameter		Note
Production Function Coefficients	α_m, α_l	From Input Cost Share of Non-Self Generators (see equations (10) and (11))
	α_k	Constant Return to Scale
	γ	Electricity Input Cost Share
Price of Grid Power	$p^{E,G}$=4.5	World Bank Survey
Price of Self-Generated Power	$p^{E,S}$=7	World Bank Survey
Shortages	δ	Data collected from Central Electric Authority
Prices of Output, Labor, Materials	$p = 1$, $p^L = 1$, $p_M = 1$	Normalization

Table 14: Prediction Output Loss from Electricity Shortages

Shortage	7.2%
Loss in Output for Non-Generators	9.7%
Loss in Output for Generators	0.9%
Unweighted Loss in Output	5.4%
Weighted Loss in Output	6.5%
Loss in Measured TFP for Non-Generators	0.0%
Loss in Measured TFP for Generators	2.4%
Loss in Measured TFP	1.2%

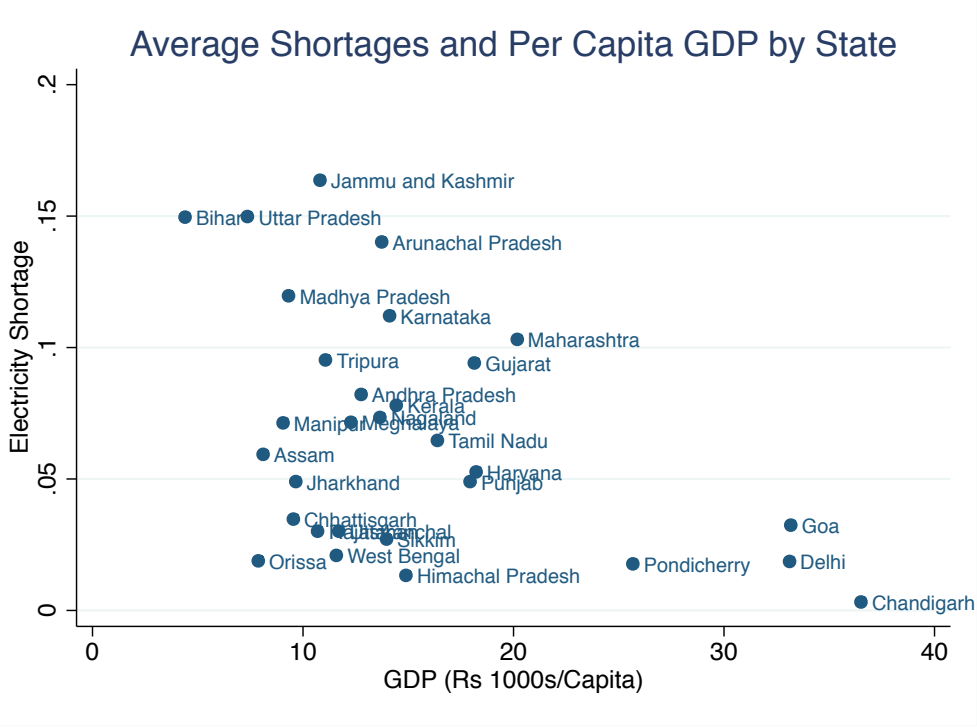
Note: Prediction from the ASI for 2005 using the model described in text. Weighted average refers to the average weighted by plant output. TFP defined as the residual of the sales generating production function using the approach described in section 3.

Figure 1: Average Shortages from 1994-2008



Notes: This figure presents each state's average electricity shortage for 1994-2008, as estimated by the Central Electricity Authority. Darker colors indicate more severe shortages. Thicker state lines on the map demarcate the five electricity grids: Northern, Southern, Eastern, Western, and Northeastern.

Figure 2: Shortages and per Capita GDP



Notes: This figure plots each state's average shortage and average per capita GDP (in real 2004 Rupees) over all years of our sample.

Figure 3: Variation in Shortages Over Time

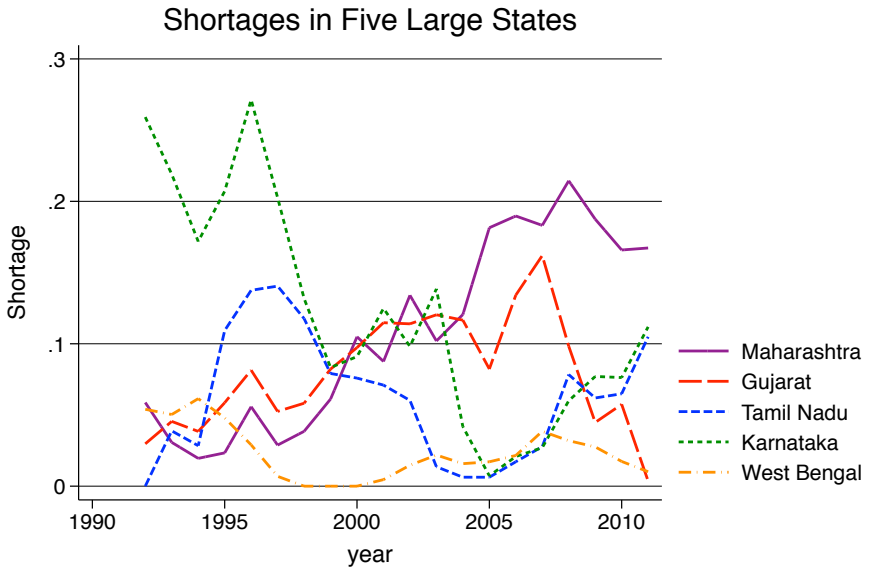


Figure 4: Manufacturing Electricity Generation in India vs. the U.S.

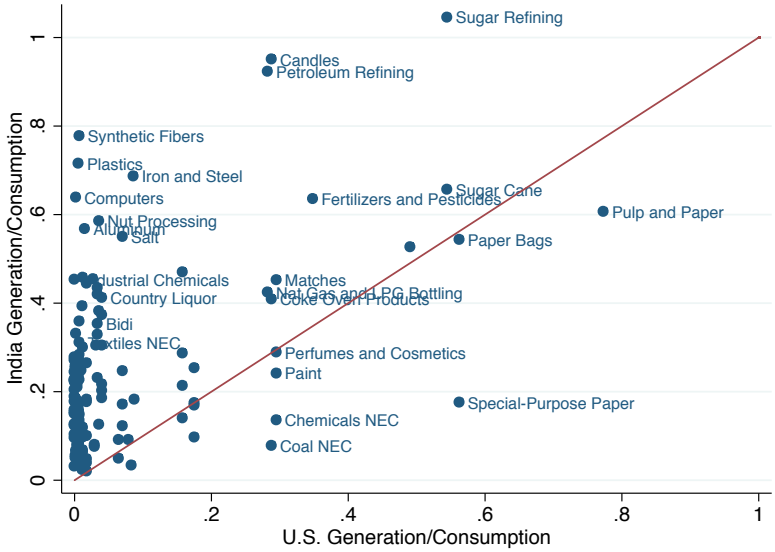


Figure 5: Self-Generation and Shortages

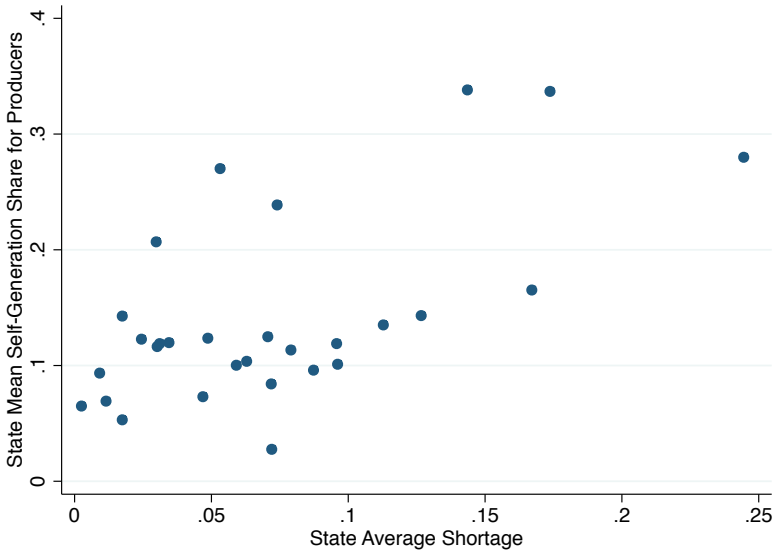
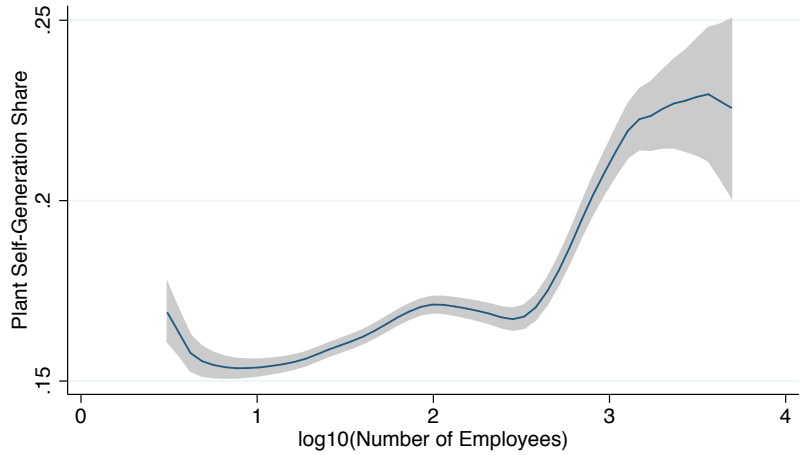
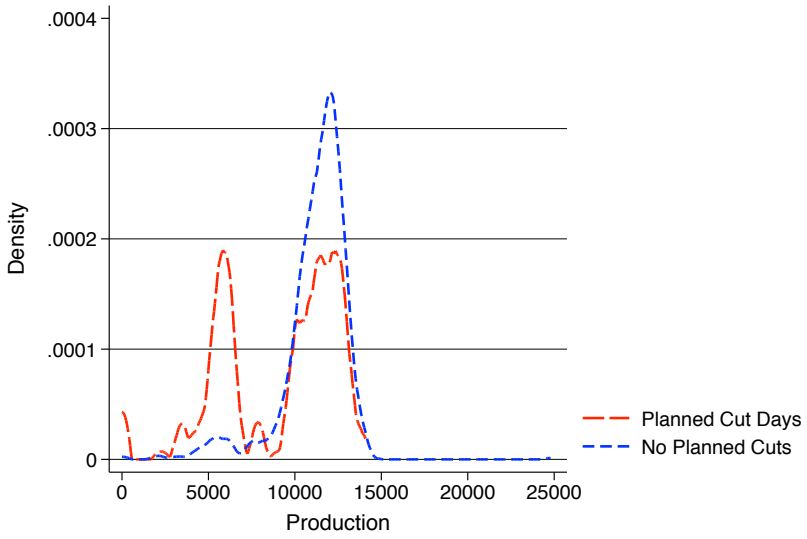


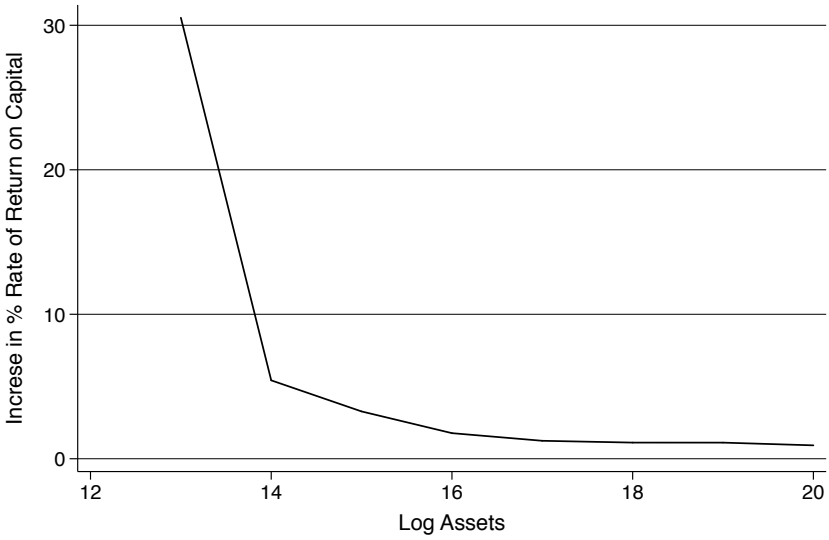
Figure 6: Self-Generation and Plant Size



Notes: This figure shows the share of plants that self generate and, for the plants that do self-generate, the share of electricity use that is self-generated, as a function of number of employees. The figure includes all plants with more than two and fewer than 10,000 employees.

Figure 7: Output on Power Holidays and Non-Holidays





Note: Rate of return on capital is the ratio of change in profits from eliminating shortages over capital stock. Median presented.

Figure 8: Increase in Rate of Return on Capital from Eliminating Shortages

Online Appendix: Not For Publication

How Do Electricity Shortages Affect Productivity? Evidence from India
Hunt Allcott, Allan Collard-Wexler, and Stephen D. O'Connell

A Annual Survey of Industries Data Preparation

We extract from the raw data a subset of all variables available separately for each year and then stack all years of data together. [21] We first correct accounts for 1995-96 to 1997-98 whose values have been supplied in "pre-multiplied" format from CSO/MOSPI. We then merge in state names based on the coding schemes provided with the ASI documentation, and create a separate consistently-defined state variable which takes into account the creation of Jharkhand, Chhattisgarh and Uttaranchal (now Uttarakhand) in 2001 from Bihar, Madhya Pradesh and Uttar Pradesh, respectively.

India classifies manufacturing establishments by National Industrial Codes (NIC), which resemble industrial classifications commonly used in other countries. The classifications were revised in 1987, 1998, 2004, and 2008. We convert all industry classifications to the NIC-1987 scheme using concordances provided by MOSPI with the data purchase.

All financial amounts are deflated to constant 2004-05 Rupees. Output is deflated by a three-digit commodity price deflators as available in the commodity-based table "Index Numbers Of Wholesale Prices In India – By Groups And Sub-Groups (Yearly Averages)" produced by the GOI Office of the Economic Adviser-Ministry of Commerce & Industry collected for the period of 1979-80 to 2009-10 (OEA 2013). Each three-digit NIC-1987 code is assigned to a commodity listed in this table, which are used to deflate directly output (depending on a plant's NIC-1987 code), fuels accounts are deflated using the "fuel, power, light and lubricants" commodity category. To deflate material inputs, we construct the average output deflator of a given industry's supplier industries based on India's 1993-94 input-output table (CSO 2012). Electricity and other fuel inputs are deflated by the price index for "Fuel, Power, Light, and Lubricants. Capital is deflated by an implied (national) deflator calculated from "Table A-16: Sector-wise Gross Capital Formation" from the Reserve Bank of India's "Handbook of Statistics on the Indian Economy." Electricity prices are deflated using a national GDP deflator. Once deflated, we then recalculate materials costs to include fuels used for electricity generation using an approximate cost of self-produced electricity per kWh from the World Bank Enterprise Survey in Table 3.

The data do have some shortcomings. One is that while the data are representative of small registered factories and a 100 percent sample of large registered factories, not all factories are actually registered under the Factories Act. Nagaraj (2002) shows that only 48 percent and 43 percent of the number of manufacturing establishments in the 1980 and 1990 economic censes appear in the ASI data for those years. Although it is not clear how our results might differ for plants not registered under the Factories Act, the plants that are observed in the ASI are still a significant share of plants in India.

A second concern is that there are anecdotal assertions of under-reporting of value added, perhaps associated with tax evasion, by using accounting loopholes to over-state input costs or under-state input costs. As an example of these two issues, Nagaraj (2002) discusses the three digit industry classification for manufacture of semi-finished iron and steel products, where the number of factories registered dropped by more than 50 percent and value added does not grow as quickly as the value of production. As long as changes in this under-reporting are not correlated with electricity shortages, this will not affect our results.

To ensure a sufficient sample size (>100 plant-years) for our industry-by-industry estimation of median cost shares, we aggregate together a small number of three-digit NIC industries

For industries that may have available fuel feedstock with which to generate electricity, we construct a materials term that assumes the cost of generated electricity is effectively zero and use this auxiliary materials term in robustness checks.

A.1 Determination of Final Sample

The 1992-2007 ASI dataset begins with 783,804 plant-year observations. Plants will still appear in the data for any number of reasons even if they do not provide survey responses due to closure or any number of

[21] We thank Jagadeesh Sivadasan for helpful discussions and for providing Stata code that greatly facilitated the read-in of 1992-1997 ASI data. Read-in programs for ASI data from 1998 onwards were collected from the International Household Survey Network (http://catalog.ihsn.org/index.php/catalog/central; author: Olivier Dupriez, World Bank)

reasons for non-response. We drop 131,735 of these plants reported as closed or non-responsive. We drop a trivial number of observations missing state identifier codes, 18,116 observations reporting non-manufacturing NIC codes, and 19,407 observations missing the NIC code field. We remove a small number of observations (primarily in the earlier years of our dataset) which are exact duplicates in all fields, assuming these are erroneous multiple entries made from the same questionnaire form. Since we are concerned primarily with productivity, we remove 85,935 observations that are missing information on gross sales. We then inspect cost share ratios of expenditures on materials, labor and fuels to total sales value. We drop 7,859 observations with multiple cost share outliers (indicating likely underreporting of gross sales value not caught in the previous step). Finally, once this cleaning is complete, we use median regression to estimate production function parameters and calculate Cobb-Douglas productivity term given by eqn. tk. Our final sample restriction is to drop 3,316 plant-years which have a log-productivity term greater than 3.5 in absolute value from the sample median (indicating misreporting in one of the main production function fields). The final sample is comprised of 517,288 plant-years, of which 306,809 are from the sample scheme plants and 210,479 are from the census scheme. Appendix Table Atk shows the above-described process in tabular format.

A.2 Data Cleaning

We also intensively inspect a number of the variables used throughout our analysis to ensure data quality and flag values which are likely misreported. This process results in a number of flags in the data which are used to restrict the sample according to the requirements of the specific analysis.

- We flag observations with high cost shares: for labor, materials, and fuels this corresponds to having the ratio of the input cost greater than twice reported output value. For electricity, observations are flagged is the cost share if greater than reported sales. For any observations satisfying these criteria, the underlying fields are made missing so that in the case that they survive other sample drops they will not figure into any regression analysis.
- We perform a similar analysis for labor and electricity using reported physical quantities which imply cost shares greater than 200 percent of sales, making missing the underlying reported physical quantity fields if the implied cost shares are too high.
- There are a trivial number of observations which report unrealistic count of persons engaged, which we make missing in those cases.
- Finally, we flag observations that exhibit large year-to-year fluctuations in the main production function accounts (output, materials, labor, electricity, fuels). We flag observations at two levels: if the change in logged value in a given field is more than 1.5 or 3.5 from the observed values in adjacent year. This procedure applies only to plants observed in consecutive years, and we only construct the flags in the data in order to restrict the samples as a robustness check rather than make missing the underlying values of these accounts.

A.2.1 Cleaning Electricity Variables

Our analysis focuses specifically on electricity inputs, so it was imperative to pay particular attention to these and related fields (quantity consumed, quantity and value purchased, quantity self-produced, quantity and value of all fuels consumed).

- We impute missing values for a small number of plants that report zero electricity consumption
- We flag observations and make missing their electricity fields if they report consuming more than 110 percent or less than 90 percent of the total amount of electricity they report purchasing and generating.

- We make missing the value of electricity sold if the implied sales price per KwH is less than 2 percent or more than 5000 percent of the median grid electricity price calculated across plants the same state and year. We also make missing the reported quantity of electricity sold if this price flag is triggered.
- We make missing the value of electricity purchased plus produced is more than 110 percent or less than 90 percent of the quantity of electricity consumed.
- We make missing the quantity and value of electricity purchased if the implies purchase price per kilowatt-hour is less than 2 percent or more than 5000 percent of the median grid electricity price calculated across plants the same state and year. We also make missing the reported quantity of electricity purchased if this price flag is triggered.

A.2.2 Production function coefficient estimations

We use quantile (median) regression to recover production function coefficients and measures of electricity intensity by industry. We separately estimate a median regression for each two-digit industry, allowing for a linear time trends and separate intercepts for each underlying three-digit industry. This estimation is performed only on plants that do not report self-generation. To ensure sufficient sample size in each three-digit industry we adjust slightly industry definitions to ensure each three-digit industry has at least 100 plant-year observations.

Once these coefficients are initially recovered, they are used to estimate (Cobb-Douglass) productivity. Productivity outliers are then dropped from the sample according to Section tk, and the production function coefficients are then restimated by the method described above.

B Appendix Tables and Figures

Figure A-9: Annual Hydro Electricity Production for Five Large States

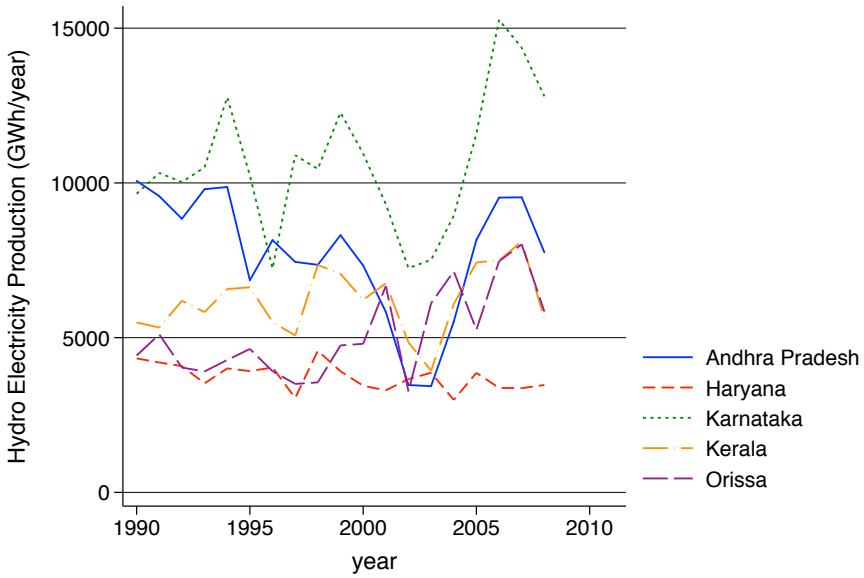
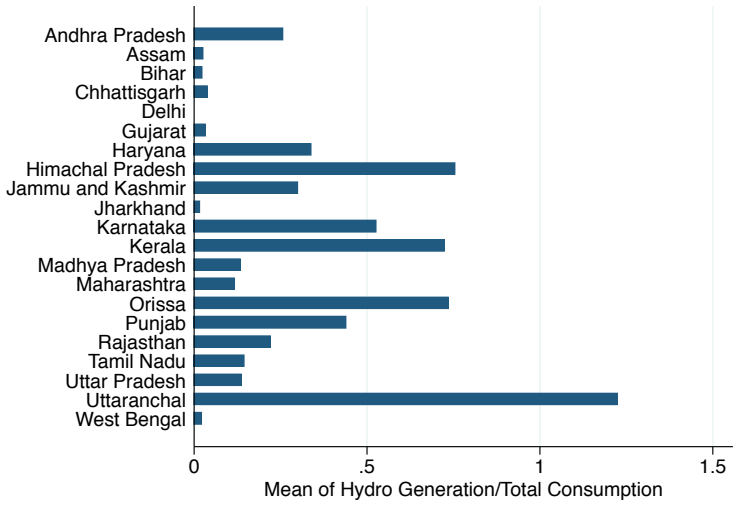
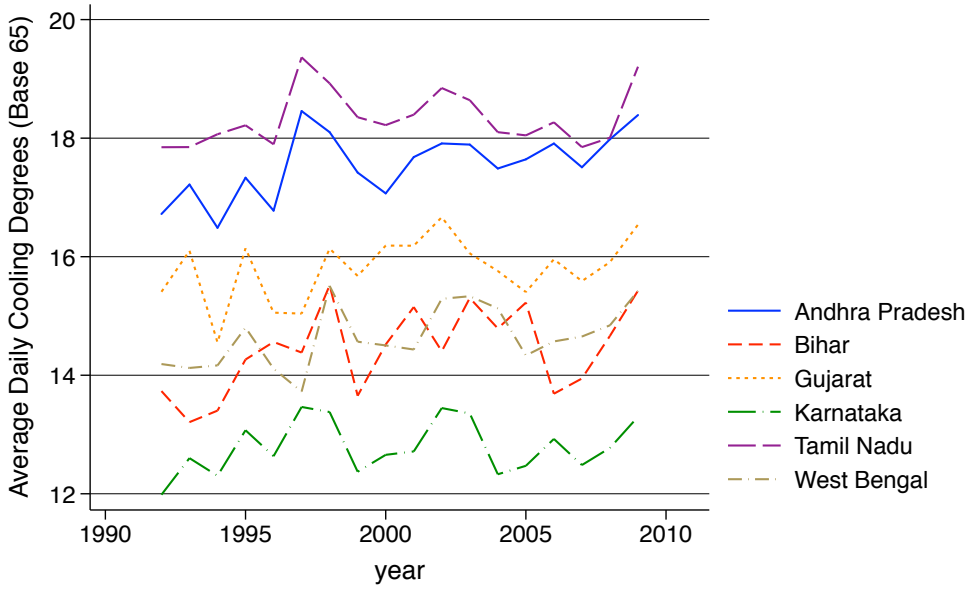


Figure A-10: Hydro Electricity Consumption Share by State



Notes: This figure presents the mean across all observed years of states' ratios of hydroelectricity production to total consumption. The figure includes only larger states with GDP larger than one billion Rupees in the year 2004 and with non-zero manufacturing production.

Figure A-11: Annual Cooling Degrees for Six Example States



Notes: This figure presents the annual cooling degrees for six example states.

Table A-15: Cross-Sectional Correlations in the 2005 WBES

	(1)	(2)	(3)	(4)
	Percent Loss	1(Own Generator)	Self-Gen Share	1(Top Problem)
ln(Number of Cuts)	0.774	0.048	1.599	0.041
	(0.172)***	(0.008)***	(0.287)***	(0.007)***
R^2	0.02	0.02	0.02	0.02
N	1,629	1,633	1,626	1,676

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-16: Generators and Non-Generators

	(1)	(2)	(3)	(4)
LHS Variable:	ln(Output)	ln(Output)	ln(TFP)	ln(TFP)
D.Shortage	-0.587	-1.212	-0.655	-1.112
	(0.415)	(1.065)	(0.468)	(0.761)
N	124,550	60,411	122,782	59,098
Electricity Producers	Yes	No	Yes	No

Notes: This table presents instrumental variables estimates of Equation (22), separately for establishments that produce electricity in any year ("Producers") vs. those that do not. Standard errors clustered by state and year. *,**, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively.

Table A-17: Small vs. Large Plants

	(1)	(2)	(3)	(4)
LHS Variable:	Self-Gen Share	ln(Fuel Input Cost Share)	ln(Output)	ln(TFP)
D.Shortage	-1.989	-20.594	-4.318	0.940
	(0.932)**	(17.842)	(3.949)	(2.349)
D.ShortagexmedianlnY	0.154	1.324	0.206	-0.103
	(0.061)**	(1.081)	(0.223)	(0.137)
N	96,708	97,546	184,830	181,752

Notes: This table presents instrumental variables estimates of Equation (22) while additionally including the interaction of Shortage and the establishment's median log output. Standard errors clustered by state and year. *,**, ***: Statistically different from zero with 90, 95, and 99 percent confidence, respectively.

Table A-18: Robustness Checks for Average Effects: Electricity Intensity λ

	(1)	(2)	(3)	(4)
	Include Outliers	Limited Outliers	Lags and Shortage	Leads
D.Shortage	-0.000	-0.001		-0.001
	(0.002)	(0.002)		(0.002)
D.PeakShortage			0.002	
			(0.001)**	
D.lagShortage				0.001
				(0.002)
D.leadShortage				-0.002
				(0.002)
N	175,477	167,360	174,532	160,219

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-19: Robustness Checks for Average Effects: Self-Generation Share

	(1)	(2)	(3)	(4)
	Include Outliers	Limited Outliers	Lags and Shortage	Leads
D.Shortage	0.188	0.200		0.207
	(0.050)***	(0.049)***		(0.048)***
D.PeakShortage			0.038	
			(0.021)*	
D.lagShortage				0.113
				(0.051)**
D.leadShortage				0.074
				(0.038)*
N	119,214	86,824	96,025	88,448

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-20: Robustness Checks for Average Effects: Fuel Intensity

	(1)	(2)	(3)	(4)
	Include Outliers	Limited Outliers	Lags and Shortage	Leads
D.Shortage	1.034	0.630		0.906
	(0.333)***	(0.208)***		(0.218)***
D.PeakShortage			0.084	
			(0.122)	
D.lagShortage				0.025
				(0.194)
D.leadShortage				-0.336
				(0.221)
N	98,800	90,643	96,801	95,845

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-21: Robustness Checks for Average Effects: Output $\ln(Y)$

	(1)	(2)	(3)	(4)
	Include Outliers	Limited Outliers	Lags and Shortage	Leads
D.Shortage	-0.086	-0.019		-0.051
	(0.066)	(0.058)		(0.068)
D.PeakShortage			-0.038	
			(0.030)	
D.lagShortage				0.057
				(0.068)
D.leadShortage				0.089
				(0.066)
N	184,445	180,841	184,033	168,810

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-22: Robustness Checks for Average Effects: Productivity

	(1)	(2)	(3)	(4)
	Include Outliers	Limited Outliers	Lags and Shortage	Leads
D.Shortage	0.019	0.033		0.033
	(0.063)	(0.048)		(0.061)
D.PeakShortage			-0.033	
			(0.027)	
D.lagShortage				0.056
				(0.060)
D.leadShortage				-0.055
				(0.053)
N	181,257	177,986	180,947	165,894

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A-23: Data cleaning steps and sample drops

Step	**Dropped obs.**	**Sample Size**
Start		783,804
Closed plants	-131,735	652,069
Missing state codes	-2	652,067
Non-manufacturing NIC codes	-18,116	633,951
Missings NIC code	-19,407	614,544
Exact duplicates	-146	614,398
Missing gross sales value	-85,935	528,463
Multiple cost share outliers	-7,859	520,604
Productivity outliers	-3,316	517,288
Final obs count, 92-07		517,288
For panel dataset, drop sample scheme	-306,809	210,479