Costly Blackouts? Measuring Productivity and Environmental Effects of Electricity Shortages*

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Abstract

Input factor reliability may substantially limit a firm's ability to produce in a least-cost manner. These productivity losses may manifest as a change in a firm's decision of what to produce in-house (versus purchase from firms with more reliable inputs), or the level of technical efficiency a firm adopts. We examine these issues by looking at electricity blackouts which affect a firm's production capabilities, especially in developing countries. In particular, this paper examines electricity reliability in China during a period of severe shortages. Starting in 2002, the fast-growing Chinese demand for power, coupled with regulated prices, led to blackouts that varied in degree over space and time. By prioritizing residential and commercial use, regulatory agencies arranged for rolling blackouts of industrial enterprises. We examine how these shortages affected industrial productivity and what the implications were for the environment. Incorporating a measure of electricity reliability into a cost function, we measure the factor-neutral and factor-biased effects of scarcity on productivity. Our data consist of 1340 Chinese energy-consuming industrial enterprises in eleven sectors from 1999-2004. Our results suggest that enterprises re-optimized among the factors in response to electricity scarcity by shifting from energy (both electric and non-electric sources) into materials—a shift from "make" to "buy." We do not find evidence of an increase in self generation as a result of scarcity. The results are robust for alternative scarcity measures and alternative specifications.

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1. Introduction

A firm's productivity, where it locates, what it produces, what it outsources will be shaped by what resources are available and how reliable are those inputs. Throughout the developing world, electricity reliability remains a hurdle for economic growth. In this paper, we examine how substantial resource adequacy issues have shaped how industries in China produce, what these production distortions cost firms, and what were their implications for carbon emissions.

From the late 1990s through the middle of the 2000s, 26 of the 30 Chinese provinces experienced blackouts associated with resource scarcity issues. The fast-growing economy was outstripping the growth in new power supply, many energy prices were regulated through price caps, and residential and commercial sectors were given priority. As a result, many industrial companies were affected by blackouts. For example, the Eastern grid (one of the six transmission regions) curtailed over 13,000,000 MWh, or over two percent of load, in 2004 alone; in contrast, the rolling blackouts of California crisis in 2000-2001 curtailed less than one 1000th that amount.[1]

Facing reliability issues, firms may change their factor inputs. They may decide to self generate, outsource production of intermediate goods, or improve technical efficiency. They may also experience total factor productivity losses if they must continue with their historic input mix. In this paper, we examine these issues by combining several Chinese datasets with information on facility production, facility energy use, and regional power grid reliability. Our data consist of 1340 Chinese energy-

[1] Eastern China consumes about 2.5 times more power than California. Data on the level of power curtailed are from personal interviews with China's Eastern Grid Company and the California Public Utilities Commission (http://docs.cpuc.ca.gov/word_pdf/misc/generation+report.pdf accessed June 20, 2008), respectively.

consuming industrial enterprises in eleven sectors from 1999-2004. We estimate a flexible cost function, incorporating a measure of electricity scarcity to test these hypotheses.

Our results suggest that enterprises re-optimize among the factors in response to electricity scarcity. Namely, they shift from energy expenditures (from both electric and non-electric, primary energy sources) into material expenditures. This is consistent with the hypothesis of outsourcing: enterprises in regions where power has become less reliable shift from "make" to "buy" in obtaining intermediate goods. We do not find evidence that electricity scarcity lead to an increase in self generation. The results are robust for alternative scarcity measures and alternative specifications.

This paper relates to several literatures. The first studies incomplete product availability from stock outs. Conlon and Mortimer (2010) note that in markets where goods are perishable, seasonal, or expensive to store—like electricity, or vending machines in their case—stock outs may be common and important features. Conlon and Mortimer discuss the stock out literature that examines how inventory management can dampen recessions (McCarthy and Zakrajsek, forthcoming), and affect vertical relationships (Narayanan and Raman, 2004) and price competition (Balachander and Farquhar, 1994). Firms may respond by smoothing production and storing goods (Abel, 1985) or by contracting with multiple suppliers (Dick, 1992). In the case of electricity, neither option is applicable as the good cannot be stored and is delivered over a common network. Operations research studies a related literature of supply chain management.[2]

Another related literature examines the management of unreliable resources in developing countries. For example, Mexican households manage unreliable water

[2] For a review of this literature, see de Kok and Graves (2003).

services using *tinacos* storage devices (Baisa, Davis, Salant and Wilcox, forthcoming). Unlike water, power is prohibitively expensive to store and firms must respond in other ways. Several papers have studied the economic costs of blackouts, particularly in developing countries. Jyoti, Ozbafli, and Jenkins (2006) review this previous literature.[3]

Our paper proceeds as follows. Section 2 provides the background on the Chinese blackouts. Section 3 discusses the theory of how factor reliability may change production. In section 4, we lay out the empirical model and discuss the data. Section 5 reports the results. In section 6, we offer concluding remarks.

2. Background

Over the past few decades, the Chinese power supply sector has experienced a boom-bust cycle. Reform initiated in 1985 led to the transfer of control of electric power generation from the central government to local governments and firms. This provided these energy suppliers with an incentive to invest in new power generation. A rapid increase in the construction of new power plants followed throughout the mid-1990s to the point that there was substantial over-supply of power capacity (OECD/IEA, 2006). The Chinese government reacted by imposing a moratorium on the construction of new power plants in 1999, which ultimately caused a severe shortage of electric power after 2002 when the demand for electricity—caused by China's construction boom—rose rapidly. Power availability and reliability was further aggravated during this time by unusually hot summers and cold winters, extreme weather events such as snow storms in the mid South, and a shortage in coal supply (Lin *et al.*, 2005; Wang, 2007).

[3] For example, see Munasinghe and Gellerson (1979), Munasinghe (1979), Swan (1980), Bental and Ravid (1982), Beenstock and Goldin (1997), and Billinton and Wangdee (2005).

A number of mechanisms were utilized to respond to these shortages. First, pricing tools commonly used elsewhere in the world, such as peak-load pricing, were instituted to smooth the load between peak and off-peak times. But their effectiveness was limited by regulatory control on prices and the slow installation of real-time meters. Supply-side policies were also implemented in an attempt to expand generation: the National Development and Reform Commission authorized the construction of new power plants and the expansion of the grid system, all backed by favorable financing packages offered through the state-owned banks. However, given the long construction cycle, the effects of these supply-side efforts were not felt immediately. As a result, rationing quota and rolling blackouts were the more widely used mechanism to address these shortages. Planned outages and changes in production schedules were imposed to deal with the shortages, causing some firms to resort to diesel-powered self-generation in response.[4] This led to a 16 percent increase in oil demand in 2004, accounting for 27 percent of the increase in world oil demand in that year (Rosen and Houser, 2007; OECD/IEA, 2006).

In 2002, China had six main regional grids—Central, East, North, Northeast, Northwest, South—each encompassing several provinces.[5] Within each grid, the transmission of power is frequent and with minimal congestion. However, in the absence of long distance transmission DC lines, the transfer of electric power among grids has been difficult. As a result, in tight markets, provinces are able to provide power to other provinces located within the same regional grid through load management, but the sharing of power across grids to meet peak demand is, in most cases, impossible. Grid

[4] http://www.smexm.gov.cn/2005-6/2005612102317822.htm. Accessed April 12, 2007.
[5] Grid systems in Xizang (Tibet) and Taiwan are not connected with China's national grid system.

level performance indicators are, therefore, a meaningful way to measure the extent of power system reliability, or scarcity, within a region.

The number of provinces reporting power interruptions is also a meaningful indicator to measure system reliability. Table 1 shows the number of provinces that reported power interruptions (blackouts) by grid and year. Out of the 30 Chinese provinces, 12, 22, and 26 experienced blackouts in 2002, 2003, and 2004, respectively. Although Table 1 only reports occurrences and not the duration or frequency of blackouts, the Central and Eastern grids followed by the Southern grid have experienced the most blackouts over this period.

Figure 1 shows the influence of brownouts on service reliability measured in percentage terms for the years 1998 to 2005 (Chen and Jia, 2005). Many news reports and case studies have suggested large economic costs as a result of these brownouts or blackouts, although they are mostly based on isolated case studies or surveys. For example, Zhejiang Province in the Eastern Pearl River Delta reported costs related to blackouts to be 100 billion RMB or approximately nine percent of gross regional product in 2004.[6] In another study, Lin *et al.* (2005) surveyed enterprises in six provinces and estimated the marginal cost of one hour of outage to be 78,482 RMB or 10,000 US dollars.

Contributing to these shortages is the demand for electric power which has seen a dramatic rise since 2000, growing by 41 percent between the years 2000 and 2007 (USDOE/EIA, 2009). Most of this recent growth is attributable to increases in the demand for electricity from the manufacturing sector which is experiencing astronomical

[6]Chinese Business Times. (Dec. 12, 2004) http://finance.sina.com.cn/g/20041222/03001241424.shtml1. Accessed April 14, 2007.

growth in demand for construction-related products (*e.g.*, steel and cement) as a result of China's recent spike in construction. However, increases in household demand for electricity have also contributed: household demand for electricity grew by 11.7 percent annually between 2000 and 2006. Household demand comprises 11 percent of total electricity consumption in 2006, slightly down from 12 percent in 2000. Electricity demand in the manufacturing sector, on the other hand, comprises 74 percent of total electricity consumption in China in the year 2006, up from 71 percent in 2000 (NBS, 2007).

Electricity is the dominant source of energy in the manufacturing sector, comprising more than 40 percent of primary energy consumption in the sector, while coal comprises approximately 25 percent. As a result, the manufacturing sector in China is extremely vulnerable to shortages in electricity supply. Depending upon a firm's ability to substitute to alternative forms of energy, this reliance on electricity may result in manufacturing firms taking the full brunt of electricity shortages. For example, extra costs may be incurred due to the need to re-arrange production schedules. Alternatively, firms may choose to self-generate which will require additional capital and diesel purchases. This may particularly be true for industries at the top of the rolling blackouts list. During these periods of shortages, many light industries, such as food processing or textiles, were among the first to face electricity quotas. Many of these enterprises were reported to be working only four days a week or working during off-peak hours (Natural Resources Defense Council, 2003; World Bank, 2005, Thompson, 2005).

These shortages have a number of possible environmental implications. Electric power generation in China is almost completely coal-based. Currently, 82 percent of installed generation capacity is fossil-fuel based, of which 97 percent is coal. Hydropower comprises 15 percent of total installed capacity, while nuclear and other renewables (primarily wind) comprise two percent and less than one percent, respectively. This composition of electric power generation is in stark contrast with other countries; *e.g*., in the U.S., 49 percent of installed capacity is coal-fired, 20 percent is gas-fired, seven percent is hydropower and 19 percent is nuclear, while in India, coal comprises 68 percent of installed capacity, and the share of natural gas, oil, hydropower, and nuclear in installed capacity is 8, 4, 15, and 3 percent, respectively.

Most coal consumed in China (approximately 55 percent) is for electric power generation (OECD/IEA, 2007). Therefore, the lack of capacity for electricity is likely to result in lower emissions of pollutants related to coal (*e.g*., sulfur dioxide, nitrogen oxides, particulate matter, and carbon dioxide) than if electricity demand was fully met. However, the response of firms to self-generate in reaction to these shortages can partly offset these reductions and perhaps exacerbate local environmental problems since these self-generators are less efficient and are more likely to be located (and therefore emitting) in or close to urban areas.

3. Theory

We define the firm's problem as one of constrained optimization. We assume that a firm's output y is generated by the production function, $y=f(k,l,m,e,n;\ \theta)$, where k is capital inputs, l is labor inputs, m is material inputs, e is electricity inputs, n is other energy inputs (such as coal, oil, and natural gas) , and θ is the probability of a blackout (resource inadequacy or unreliability). Suppose that electricity is reliable, *i.e.*, θ=0. For a given set of input prices, we define the firm's dual unconstrained cost function as

$$c_u = c_u\left(p_k, p_l, p_m, p_e, p_n, y\right) \tag{1}$$

From Shephard's Lemma, we know:

$$x^* = \partial c / \partial p_x \qquad x = k,l,m,e,n \tag{2}$$

Assuming a log-linear form of the production function (such as Cobb-Douglas or translog),

$$\ln c_u = \ln c_u\left(p_k, p_l, p_m, p_e, p_n, y\right) \tag{3}$$

we can derive an expression for the value share of factor inputs; *i.e.*,

$$\frac{\partial \ln c_u}{\partial \ln p_x} = \frac{\partial c}{\partial p_x}\frac{p_x}{c} = \frac{p_x x^*}{c} \qquad x = k,l,m,e,n \tag{4}$$

Suppose there is some probability, θ>0, that electricity is unreliable. In particular, let $\hat{e}$ be the constrained level of electricity associated with periodic blackouts: $0 \leq \hat{e} < e^*$. In this constrained case, the cost function is therefore,

$$\ln c_c = \ln c_c\left(p_k, p_l, p_m, p_e, p_n, y, \hat{e}\right) \tag{5}$$

where, although the price of electricity enters into the constrained cost function, it does not enter into the firm's marginal decisions as a result of the constraint on electricity availability. For a risk neutral firm, the expected log cost function for producing a given amount $\overline{y}$ is

$$E[\ln c(\overline{y})] = (1-\theta)\ln c_u(\overline{y}) + \theta \ln c_c(\overline{y}) \tag{6}$$

The effect on total factor productivity (TFP) is therefore likely to be negative, resulting in greater costs, as the constraint on electricity limits a firm's choices:

$$\frac{\partial E[\ln c]}{\partial \theta} = \ln c_c(\bar{y}) - \ln c_u(\bar{y}) > 0\,. \tag{7}$$

In order to determine the effect of blackouts on the expected value shares, *i.e.*, $vsh_x \equiv \frac{p_x x}{c}$, we compute the partial derivative of equation (4) with respect to θ. For electricity, this is negative as the price of electricity does not enter the constrained marginal cost function:

$$\frac{\partial vsh_e}{\partial \theta} = \frac{\partial^2 \ln c}{\partial \ln p_e \partial \theta} = \frac{\partial \ln c_c}{\partial \ln p_e} - \frac{\partial \ln c_u}{\partial \ln p_e} = -\frac{\partial \ln c_u}{\partial \ln p_e} < 0. \tag{8}$$

For the other inputs, the sign depends on whether the input is a substitute for or complement of electricity.

Firms may decide to self-generate electricity once blackouts become more common. This would result in an increase in the firm's use of other energy sources such as diesel oil and greater use of capital. In this case, other energy and capital are substitutes for purchased electricity; *e.g.*,

$$\frac{\partial vsh_n}{\partial \theta} = \frac{\partial^2 \ln c}{\partial \ln p_n \partial \theta} = \frac{\partial \ln c_c}{\partial \ln p_n} - \frac{\partial \ln c_u}{\partial \ln p_n} > 0. \tag{9}$$

Another response to blackouts may be to outsource a portion of production. Firms may decide to purchase intermediate goods rather than produce these goods from raw materials. In this case, materials would be a substitute for electricity: $\frac{\partial \ln c_c}{\partial \ln p_m} > \frac{\partial \ln c_u}{\partial \ln p_m}$. In addition, outsourcing could result in less use of labor, capital, and other energy sources in the production of these intermediate goods. For example, a firm requiring steel as an input to production may either purchase the raw inputs (*e.g.*, pig iron, coal and electricity) to manufacturing the steel in-house or, if electricity is unreliable, the firm may decide to purchase the steel from other producers. In this case, as these other inputs are not longer needed due to outsourcing, these inputs would be complements of electricity.

Finally, firms may respond to the shortage of electricity by improving their overall energy efficiency. This would especially be the case if there were policies promoting energy efficiency at the regional level. In this case, the value share of capital would likely increase while the shares of electricity and other energy inputs would fall.

Four hypotheses emerge from the theoretical discussion above:

I. **Decreased Productivity:** From equation (7), we expect that blackouts will increase total costs.

II. **Self-generation:** One possible response to blackouts would be for the firm to self-generate. This would imply a substitution away from electricity toward non-electric energy and capital.

III. **Outsourcing:** Another possible response to blackouts would be for the firm to outsource more and thus produce less in-house. This would imply more material use and less use of the other factors of production.

IV. **Efficiency:** Blackouts are also likely to induce more energy efficiency; therefore, we expect a reduction in both types of energy and an increase in capital.

4. Empirical Model

4.1 Model of Productivity

We examine the productivity response to blackouts by measuring both factor-neutral and factor-biased effects. The standard approach to measuring neutral and factor-biased effects involves the estimation of production functions or dual cost functions. The theoretical connection between production or cost functions and factor demands makes this approach fitting for the measurement of factor bias. The choice of whether to use the production function approach or the cost function approach depends on the relevant set of exogeneity assumptions. For the production function formulation – which incorporates quantities of output and inputs – input quantities are assumed to be exogenous, whereas in the cost function formulation input prices are assumed to be exogenous. In highly aggregated data sets, input prices are likely to be endogenous and therefore a production function may be more appropriate. At the firm level, however, choices of factor inputs are likely to be endogenous while factor prices are more likely to be set in the market and therefore plausibly exogenous. Since our data set allows us to impute factor input prices for the individual firms,[7] we use the cost function approach. To test the assumption of price exogeneity, we also use average factors prices—by year, industry, and region, to re-estimate our model.

To measure productivity changes, we use a translog cost function which is the most flexible of functional forms. For firm *i*; input factor *j=k,l,m,e,n*; industry *g*; and year *t=1999-2004*, we estimate the following equation:

[7] The data set includes both quantities and values and therefore an average price can be imputed by dividing value by quantity.

$$\ln C_{it} = f(Q_{it}, p_{ijt}) = \sigma \ln S_{it} + \sum_{j=1}^{J} \theta_j \ln S_{it} \ln P_{jit} + \sum_{j=1}^{J} \alpha_j \ln P_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \beta_{jk} \ln P_{jit} \ln P_{kit}$$
$$+ \kappa \ln Q_{it} + \frac{1}{2} \delta \ln Q_{it}^{\ 2} + \sum_{j=1}^{J} \varphi_j \ln Q_{it} \ln P_{jit} + \sum_{j=1}^{J} \sum_{g=1}^{G} \lambda_{jg} D_g \ln P_{jit} \qquad (10)$$
$$+ \sum_{j=1}^{J} \sum_{t=1}^{T} \gamma_{jt} D_t \ln P_{jit} + \eta_i + \mu_{gt} + \varepsilon_{it}$$

where

C ≡ total cost of production,

Q ≡ gross value of industrial output in constant prices,

P_K ≡ price of fixed assets, calculated as (value added - wage bill - welfare payments)/(net value fixed assets),

P_L ≡ price of labor, calculated as (wage bill + welfare payments)/employment,

P_E ≡ price of aggregate energy, calculated as (energy expenditures)/(quantity of energy purchased in standard coal equivalent (SCE)),

P_M ≡ price of materials, calculated as the weighted average of industry prices using input-output shares from the national accounts,

S ≡ scarcity measure described in Section 4.3 below,

D_g ≡ industry dummies, g = mining, food, textiles, timber, petroleum products, chemicals, rubber, non-metallic metals, metal products, machinery, and other industry,

D_t ≡ year dummies, t = 1999-2004.

Therefore, parameter σ measures the factor-neutral effect and θ_j the factor-biased effects of scarcity. The null hypothesis is that production is not affected by scarcity either through factor adjustments or by making overall factor neutral changes; *i.e.*, $\sigma = 0$ and $\theta_j = 0$.

Because equations (10) and (11) represent a system of equations in which shocks to the factor shares are likely to be correlated across the error structure of the model and to gain efficiency in the estimation, the system is estimated as a seemingly-unrelated regression (SUR). Recall from (4), $vsh_j = \dfrac{\partial C_{it}}{\partial P_{jit}}$ which implies:

$$vsh_j = \theta_j S_{it} + \alpha_j + \frac{1}{2}\sum_{k=1}^{J} \beta_{jk} P_{kit} + \varphi_j Q_{it} + \sum_{d=1}^{D} \lambda_{jd} + \sum_{t=1}^{T} \gamma_{jt} + \xi_{jit}, \text{ for all } j. \tag{11}$$

To ensure that the coefficients exhibit the usual properties of symmetry and homogeneous of degree one in prices, we impose the following constraints:

$$\beta_{j,k} = \beta_{k,j}; \sum_{j=1}^{J} \alpha_j = 1; \sum_{j=1}^{J} \theta_j = \sum_{k=1}^{J} \beta_{jk} = \sum_{j=1}^{J} \lambda_{jm} = \sum_{j=1}^{J} \gamma_{jt} = \sum_{j=1}^{J} \varphi_j = 0. \tag{12}$$

We also assume constant return to scale which implies δ =0 and κ =1. Furthermore, in order to have an invertible disturbance covariance matrix, we drop the value share equation of materials from the estimation. To test the robustness of results, we also drop the value share equation for capital in the estimation, and estimate the model using two alternative scarcity measures described below.

4.2 Marginal Effects of Scarcity

Our cost function estimation allows us to compute the marginal and total effects of electricity scarcity on cost and carbon emissions. The calculation of the marginal change in cost due to scarcity is easily obtained from the cost equation (equation (10)); *i.e.*,

$$\frac{\partial C_{it}}{\partial S_{gt}}\frac{S_{gt}}{C_{it}}=\frac{\partial \ln C_{it}}{\partial \ln S_{gt}}=\sigma+\sum_{j=1}^{n}\theta_j \ln p_{ijt}\ ; \tag{13}$$

therefore,

$$\frac{\partial C_{it}}{\partial S_{gt}}=\frac{C_{it}}{S_{gt}}(\sigma+\sum_{j=1}^{n}\theta_j \ln p_{ijt})=\frac{C_{it}}{S_{gt}}\sigma+\frac{C_{it}}{S_{gt}}\sum_{j=1}^{n}\theta_j \ln p_{ijt} \tag{14}$$

The factor neutral effects are captured by the first term, $\frac{C_{it}}{S_{gt}}\sigma$, while the factor-biased effects are captured by the second term, $\frac{C_{it}}{S_{gt}}\sum_{j=1}^{n}\theta_j \ln p_{ijt}$.

The marginal effect of scarcity on emissions is the product of the marginal change in quantity of fuel input due to scarcity $\frac{\partial x_{it}}{\partial S_{gt}}$ and the emissions factor π_j:

$$\frac{\partial Emissions_{ijt}}{\partial S_{gt}}=\pi_j\frac{\partial x_{ijt}}{\partial S_{gt}} \tag{15}$$

The first component, $\frac{\partial x_{it}}{\partial S_{gt}}$, can be derived from equation (13) above. From the value share equations (equation (11)), θ_j represents the effect of scarcity on the value share of the input *j*; *i.e.*,

$$\begin{aligned}\theta_j &=\partial vsh_{ijt}/\partial \ln S_{gt}=\partial(x_{it}p_{ijt}/C_{it})/\partial \ln S_{gt}=p_{ijt}\partial(x_{it}/C_{it})/\partial \ln S_{gt}\\ &=\frac{p_{ijt}\partial(x_{it}/C_{it})}{(1/S_{gt})\partial S_{gt}}=p_{ijt}\cdot S_{gt}\cdot\frac{\partial(x_{it}/C_{it})}{\partial S_{gt}}=p_{ijt}\cdot S_{gt}\cdot\frac{1}{C_{it}^2}\cdot(C_{it}\frac{\partial x_{it}}{\partial S_{gt}}-x_{it}\frac{\partial C_{it}}{\partial S_{gt}})\\ &=\frac{p_{ijt}S_{gt}}{C_{it}}(\frac{\partial x_{it}}{\partial S_{gt}}-\frac{x_{it}S_{gt}}{S_{gt}C_{it}}\frac{\partial C_{it}}{\partial S_{gt}})=\frac{p_{ijt}S_{gt}}{C_{it}}(\frac{\partial x_{it}}{\partial S_{gt}}-\frac{x_{it}}{S_{gt}}\frac{\partial \ln C_{it}}{\partial \ln S_{gt}})\end{aligned} \tag{16}$$

Plugging in equation (13), $\frac{\partial \ln C_{it}}{\partial \ln S_{gt}} = \sigma + \sum_{j=1}^{n} \theta_j \ln p_{ijt}$, into equation (16), we get:

$$\theta_j = \frac{p_{ijt} S_{gt}}{C_{it}} \left(\frac{\partial x_{it}}{\partial S_{gt}} - \frac{x_{it} (\sigma + \sum_{j=1}^{n} \theta_j \ln p_{ijt})}{S_{gt}} \right). \tag{17}$$

Re-arranging, we obtain an expression for $\frac{\partial x_{it}}{\partial S_{gt}}$ in terms of parameters and other known measures such as the quantity of each factor x_{it} :

$$\frac{\partial x_{it}}{\partial S_{gt}} = \frac{\theta_j C_{it}}{p_{ijt} S_{gt}} + \frac{x_{it} (\sigma + \sum_{j=1}^{n} \theta_j \ln p_{ijt})}{S_{gt}} \tag{18}$$

We can, therefore, calculate the change in emissions due to scarcity by applying the emissions factor, π , which converts energy quantities to carbon emissions based on the carbon content of the specific energy type j :

$$\frac{\partial Emissions_{ijt}}{\partial S_{gt}} = \pi_j \frac{\partial x_{ijt}}{\partial S_{gt}} = \pi_j \left(\frac{\theta_j C_{it}}{p_{ijt} S_{gt}} + \frac{x_{it} (\sigma + \sum_{j=1}^{n} \theta_j \ln p_{ijt})}{S_{gt}} \right) \tag{19}$$

4.3 Data

The data set used in this analysis combines an industrial data set provided by China's National Bureau of Statistics (NBS) with data on electricity availability compiled from various issues of the China Electricity Yearbook. The coverage of the industrial data set is approximately 1,500 large and medium-size Chinese industrial enterprises over the years 1999-2004. The industrial data set combines two separate data sets that are updated annually by the NBS. The first is a set of economic and financial data that is collected by the Bureau's Department of Industrial and Transportation Statistics. The data include all of China's approximately 22,000 large and medium-size enterprises (LMEs) over the years 1999-2004. The second data set, also maintained by the Department of Industrial and Transportation Statistics, includes measures of approximately 20 individual energy types and aggregate measures of both the value and physical quantity of energy consumption, including the quantity of energy used for electricity generation. We derive price data from these value and quantity measures. Because this energy data set includes only the most energy intensive enterprises among the population of large and medium-size enterprises over the years 1999-2004, our combined data set includes significantly fewer observations than the first data set from which the individual firms are drawn.

Although by combining the first data set with the energy data set we lose a significant number of observations, the combined data set expands our set of factor inputs to a detailed capital, labor, energy, and materials (KLEM) data set and allows us to separate electricity consumption from non-electric energy consumption. By exploring beyond the conventional capital-labor substitution possibilities, we are able to examine the heterogeneity in factor biases from electricity shortages. The inclusion of energy in our data set allows us to explore the effects of electricity shortages on energy use and carbon dioxide emissions.

Table 2 compares levels of sales, employment, fixed assets and energy consumption in our sample (*i.e.*, the "KLEM sample") with both total industry and with the full population of 22,000 large and medium-size enterprises. As shown, although our sample represents but one percent of the number of China's industrial enterprises with annual sales in excess of five million yuan (approximately $600,000), within this group, it captures 13 percent of industrial sales, 15 percent of industrial employment, 20 percent of industrial assets, and 40 percent of industrial energy consumption.

The NBS data set classifies enterprises into 37 industrial categories. For the purposes of this analysis, we group the 37 industrial classifications into 12 industry categories and omit the electric power industry. The distribution of the number of enterprises by industry is shown in Table 3. Not surprisingly, relative to the distribution for the total population of enterprises and for just the LMEs, the energy sample includes high proportions of enterprises in the more energy-intensive industries, including the chemical and electric power industries.

The NBS data set also classifies enterprises into seven ownership classifications, consisting of state-owned enterprises and the six other non-state classifications shown in Table 4. In 1999, our sample is largely concentrated in the state-owned sector, *i.e*. 62 percent of total sales in our sample originated with SOEs. This SOE ownership bias in our sample is not surprising, since a large portion of China's energy-intensive enterprises that occupy the capital-intensive sectors are state-owned.

Our energy data set allows us to examine the influence of electricity shortages on self-generation. We construct two variables for this purpose: a self-generation rate variable and a self-generation indicator variable. The self-generation rate variable is defined as the percentage of energy used to generate electricity as a share of its total energy consumption. The self-generation indicator variable takes the value of one if the self-generation rate is positive. Examining the percentage of enterprises that self-generate electricity by grid (Figure 2), we observe that the Southern Grid has a much higher percentage of enterprises that self generate electricity than any other grids. The percentage of enterprises that self-generate changes only slightly over the years, peaking around year 2002.

Our data set also allows us to compute an enterprise's electricity intensity and the average electricity intensity for each of the eleven sectors. We calculated electricity intensity as a percentage of total energy consumption in standard coal equivalent terms. Enterprises that are more electricity intensive may respond differently to input unreliability from the less intensive enterprises. Figure 3 shows electricity intensity by sector. Less electricity-intensive sectors include textile, food, machinery, petroleum product, rubber, and timber. The more electricity-intensive group includes chemicals, non-metal products, metal products, mining, and other industries.

The industrial data set is supplemented with data on electricity shortages constructed from information obtained from various issues of the China Electricity Yearbook. These Yearbooks contain information on electricity generation and capacity from which the scarcity measures are derived. The thermal utilization rate for grid *g* at time *t* is an appropriate proxy for shortage, which is derived as:

$$S_{gt}^{Thermal} = \text{Thermal generation}_{g,t} \, / \, [\text{thermal capacity}_{g,t} * (1 - sor_{g,t} - for_{g,t})],$$

where sor_t is the scheduled outage rate and *for* is the forced outage rate. The adjustment factor (1-*sor*-*for*) is the probability of operation and (scheduled outage rate + forced outage rate) captures the probability of downtime. Power plants typically scheduled outages for maintenance and reliability purposes. For this reason, in the denominator we adjust the capacity by both forced outages due to equipment failures and scheduled outages. These utilization rates by grid and year are shown in Figure 4. For robustness checks, we also calculated the following two alternative measures of scarcity (Figures 5 and 6):

S_{gt}^{Total} = Total generation$_{g,t}$ / [total capacity$_{g,t}$* (1 - $sor_{g,t}$ - $for_{g,t}$)]

S_{gt}^{Peak} = peak load$_{g,t}$/[capacity$_{g,t}$ * (1 - $for_{g,t}$)]

Therefore, S_{gt}^{Total} is the overall utilization rate of the system and is also a proxy for the annual average probability of blackout. Its capacity adjustment factor is the same as that used in the calculation of $S_{gt}^{Thermal}$. The variable, S_{gt}^{Peak}, is a peak load blackout probability measure which a measure computed when the market is near its capacity limits. The adjustment factor is (1-*for*) where only forced outage is factored away since scheduled outages are seldom done during peak periods.

Although differences do exist among the three scarcity measures, the trends of these measures are similar. As the market got tighter after 2002, all three measures point to a higher probability of the occurrence of blackouts. These measures were also affirmed by system operators in the Eastern Grid at interviews during field work in 2007.[8] Further, as we map the industrial survey dataset with the electricity dataset geographically, we observe that these energy consuming enterprises are located in the

[8] We also develop two other measures for scarcity from the field work, but none of them has the regional variation and completeness as the three mentioned above. The first was a reliability index based on the information of brownouts from the electricity yearbooks, but it is at the national level and therefore cannot be used for firm level analysis when year fixed effects are included. We also collected data on the length and quantity of electricity interruption, but the data only exist for the Eastern Grid and cannot be applied to enterprises located in other regions.

five more prosperous grids. No enterprises are located in the less developed Northwest region.

Our data set comprises annual data and therefore does not allow us to account for the impact of duration, frequency, and timing of the interruptions which may affect the cost of production and the response of the enterprise. The data set does, however, provide us with the necessary information for productivity analysis at the annual level. Table 5 presents the summary statistics of key variables including value shares, input prices, scarcity measures, electricity intensity, and sales cost. Table 6 provides descriptive regressions of the natural log of several key variables (revenue, labor, capital, materials, electricity and nonelectric energy) on the natural log of scarcity, controlling for firm and industry*year fixed effects.

5. Results

Cost Functions

Table 7 reports the main results from our estimation of (10) and (11). The first three columns of the main specification differ in their assumption and treatment of the exogeneity of prices and electricity scarcity. Column 1 is the basic SUR result assuming the exogeneity of both scarcity and input prices. Column 2 accounts for the possible endogeneity of scarcity by using heating and cooling degree days as instruments for scarcity. Column 3 instruments input prices using the province-year average. All specifications control for enterprise and year fixed effects. All results are obtained using SUR on the system of equations with the materials equations dropped. But the results remain robust when we dropped the capital equations instead. Results are also robust to the two alternative measure of scarcity.

From our main SUR regression results, shown in the first column, the coefficient on scarcity suggests that enterprises facing greater possibilities for electricity shortages did not see a significant neutral effect on cost. Therefore, our first hypothesis that scarcity will lead to a negative effect on an enterprise's productivity as a result of the constraint on electricity availability does not hold true. However, these results do suggest that scarcity does have an effect on how enterprises produce; namely, scarcity leads to significant substitutions among the five factor inputs. Scarcity leads to a reduction in the use of labor, electricity and other forms of energy and an increase in the use of capital and materials. For a one standard deviation increase in scarcity, the cost share of materials increases by 1.1 percent while that of non-electricity energy decreases by a similar amount. Capital cost shares increase slightly while labor shares decline modestly with scarcity.

This materials-using effect of scarcity suggests that enterprises are choosing to out-source production rather than to produce in-house, consistent with our third hypothesis. We do not, however, find evidence to support our second hypothesis that electricity blackouts will lead to greater self-generation. While we do see a substitution toward capital use, we do not see a substitution toward other types of energy, in particular diesel oil, which would be consistent with self-generation. To the contrary, we see a significant reduction in non-electric energy that is much larger than the reduction in electricity. This effect on energy overall combined with our capital-using effect is consistent with our last hypothesis which predicts that the threat of blackouts will lead to capital-intensive energy efficiency improvements.

The second column of Table 7 shows the results from our instrumental variables estimation. We find in the first stage, the set of instruments—*i.e.*, heating and cooling degree days as well as their interactions with factor prices—to be strong predictors of scarcity.[9] The second stage of the IV regression is reported in Table 7 and shows that the IV results are quite similar to those of the main SUR model in the first column.

We next repeat the main results using average factor prices—by year, industry and region—to test whether enterprise-level prices exhibit measurement error. We hypothesize that average prices would be less susceptible to an errors-in-variables problem. As shown in the third column of Table 7, these results are similar to our main findings, suggesting little of any errors-in-variables problem.

Finally, the last column of Table 7 relaxes the assumption of constant returns to scale using the same econometric methodology as the rest of the table. In other words, output is treated as exogenous given firm fixed effects. We find similar factor bias results. In this specification, the factor neutral effect is large and significantly negative, suggesting that firms reduced costs in response to scarcity.

Table 8 reports tests for heterogeneous effects by including an interaction of an index of electricity intensity with the variables of interest. We find that enterprises in low electricity-intensive industries also substitute from labor to capital, as in the main results. Similarly we find that they use less non-electric energy sources. However, we do not find evidence of an increase in materials by these enterprises. For the enterprises in the

[9] A Wald test on the instruments' joint significance for the ln(scarcity) regression, for instance, returns an F-statistic of 882 (p-value < 0.001).

most electricity-intensive industries, we find an even greater increase in capital and a substantial decrease in electricity. However, contrary to the main findings, we see that these enterprises actually decrease expenditures on manufacturing. This may be the result of the lack of available options to outsource by these enterprises. As shown in Figure 3, the electricity intensive industries, such as mining and metals, may have few options to outsource intermediate products. Therefore, the option to outsource seems greater for enterprises that are less capital-intensive and electricity-intensive.

Table 9 reports our results by industry. Given sample limitations, we relax the cost function further and estimate Cobb-Douglass functions for each industry. We find large responses in electricity shares for mining. Outsourcing was large in timber (including paper, pulp, and furnature) and in metal. There were large decreases in other energy shares for most industries: mining, timber, petroleum, chemicals, and metal.

Table 10 reports the results by region. Most regions had significant changes in input shares. The north and northeast experienced large drops in other energy shares. Electricity shares dropped in nearly all regions. Conversely, material shares increased throughout the country.

Self Generation

As discussed above, our results do not support the hypothesis that enterprises will choose to self-generate in reaction to electricity shortages. We explore this further in Table 11 which reports our findings on tests of self-generation. The first column of Table 11 provides results from the estimation of a linear probability model of adoption decisions, using an indicator of self generation as the dependent variable.[10] In our linear probability model with enterprise-level fixed effects, we find that scarcity and scarcity

[10] In our sample, only 18 percent of firms self-generate electricity.

interacted with an indicator of electricity-intensive enterprises are not significant predictors of self-generation. We do find, however, that self-generation is more common when material costs increase. These results suggest that self-generation is more likely when outsourcing is costly. A probit model with enterprise random effects finds qualitatively similar effects.

Columns (3) and (4) of Table 11 examine usage of generation technology by looking at the fraction of electricity that is self-generated. Here we find that enterprises in the least electricity-intensive industries engaged in more self-generation, while those in the more electricity-intensive industries self-generated less. These results may reflect the inability of enterprises in electricity-intensive industries to self-generate enough electricity to meet their needs. Thus, these enterprises are more dependent on electricity from the grid.

Tables 12 and 13 examine self generation by industry and by region, respectively. Nonmetals were the industry most likely to use self supply power. Interestingly, the chemical industry, which may have had better access to scarce electricity during shortages, actually *decreases* self supply of power when scarcity is highest. We find this controlling for either regional average input prices and own input prices. Regionally, we see the strongest evidence of self supply in the south, but suggestive evidence in the northeast and east.

What are the overall effects of scarcity on production costs and carbon emissions? Tables 14 and 15 provide the results from our calculations of the marginal and total effects of scarcity on cost and emissions. Table 14 provides marginal and total cost figures calculated using sample averages ("average calculation") and at the enterprise-level ("enterprise-level calculation"). The results suggest that electricity scarcities over the period 1999-2004 lead to a small (albeit insignificant) decrease in total cost, driven by neutral effects that are almost completely offset by factor-biased effects. The only significant effect is the positive factor-biased effects on cost, driven mainly by materials. The shift to materials over this time period had a large positive effect on cost, as enterprises shifted to outsourcing the production of intermediate products.

Finally, Table 15 shows the effect of scarcity on emissions. From our enterprise-level calculations, electricity scarcities over the years 1999-2004 resulted in 3.4 percent reduction in emissions mainly due to reductions in non-electricity consumption which is primarily coal-based. The average calculation suggests a much smaller marginal emissions of electric power from scarcity, on the order of one percent. This discrepancy between the average calculation and enterprise-level calculation is likely the result of outliers in the energy data. Note that these environmental effects are only for the decreases in electricity and other energy consumption and do not factor in the additional emissions due to outsourcing.

6. Conclusion

This paper examines how enterprises in China respond to unreliable power supply. We find that between 1999 and 2004, when many grids became less reliable, those enterprises in regions with the least reliable power switched from using electricity to increasing their factor shares of materials, as consistent with outsourcing. We do not find evidence of an increase of self supply. In fact, we find an overall decrease in other non-electricity energy sources, suggesting that these primary energy sources are complementary inputs in producing intermediate products. We also find that enterprises facing higher levels of scarcity became more capital intensive. This, coupled with the decrease in energy use, suggests enterprises may have improved their energy efficiency.

The overall effect of blackouts, which we proxy for with a measure of scarcity, was to increase production costs. From 1999 to 2004, enterprises' costs rose by over three percent due to factor substitution biases. The reduction in demand for electricity and other energy sources, which are primarily coal, resulted in a small decrease in emissions from *these* facilities (about one percent). However, the net effect on the environment is ambiguous as outsourcing likely increases emissions from other facilities.

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Tables and Figures

Table 1: Number of Provinces with Electricity Interruption, 1999-2004

Year	Central	East	North	Northeast	Northwest	South	Total
1999	0	0	0	0	0	0	**0**
2000	0	0	0	0	0	0	**0**
2001	0	0	0	0	0	0	**0**
2002	5	4	2	0	0	1	**12**
2003	5	5	4	1	3	4	**22**
2004	6	5	6	1	4	4	**26**
Total # of Provinces	**6**	**5**	**6**	**3**	**5**	**5**	**30**

Notes: Regions are defined as in year 2004, excluding Tibet. Source: newspaper and government reports from various years.

Table 2: Shares of Industry Statistics that are Large and Medium-size Enterprises and are in the KLEM Sample in 1999

Measure	Total industry	LMEs	KLEM sample
Sales (100 million yuan)	69,851	41,166 [59%]	9,062 [13%]
Employment (10,000 persons)	4,428	3,061 [69%]	679 [15%]
Assets (100 million yuan)	71,847	53,070 [74%]	14,428 [20%]
Energy consumption (10,000 tons of standard coal (SCE))	130,119	90,797 [70%]	36,285 [40%]
No. of enterprises	162,033	22,000 [14%]	1,518 [1%]

Notes: Percentages are of total industry for a given row. KLEM sample is facilities for which we know capital, labor, energy, and materials. All industry includes industrial state owned and non-state owned enterprises with annual sales over 5 million Yuan. Assets are original value of fixed assets. Source is the China Statistical Yearbook, 2000 (NBS, 2000).

Table 3: Distribution of the Number of Enterprises by Industry in 1999

Industry classification	2-digit SIC	Total industry	LMEs	KLEM sample
Mining	06-10,12	7,257	829	113
		[4%]	[4%]	[7%]
Food and Beverage	13-16	20,125	2,593	123
		[12%]	[11%]	[8%]
Textile, apparel, and leather	17-19	20,784	2,637	93
products		[13%]	[12%]	[6%]
Timber, furniture, and paper	20-24	12,374	1,332	69
products		[8%]	[6%]	[5%]
Petroleum processing and	25	988	120	39
coking		[1%]	[1%]	[3%]
Chemicals	26-28	15,412	2,760	297
		[10%]	[12%]	[20%]
Rubber and plastic products	29-30	7,852	893	28
		[5%]	[4%]	[2%]
Non-metal products	31	14,366	1,699	242
		[9%]	[8%]	[16%]
Metal processing and products	32-34	13,644	1,429	70
		[8%]	[6%]	[5%]
Machinery, equipment, and	35-37,	29,955	6,287	162
instruments	39-42	[18%]	[28%]	[11%]
Electric power	44	4,941	1,039	213
		[3%]	[5%]	[14%]
Other industry	43,45,46	14,335	971	60
		[9%]	[4%]	[4%]
Total		162,033	22,589	1,518

Notes: Percentages are by column. Total industry includes all state and non-state enterprises with annual sales above 5 million yuan. Source: NBS (2000).

Table 4**:** Distribution of the Number of Enterprises by Ownership Type in 1999

Ownership type	Total industry	LMEs	KLEM sample only
State-owned	61,301	10,451	1,045
	[38%]	[46%]	[69%]
Collective-owned	42,585	3,381	64
	[26%]	[15%]	[4%]
Hong-Kong, Macao, Taiwan	15,783	1,567	64
	[10%]	[7%]	[4%]
Foreign	11,054	1,966	70
	[7%]	[9%]	[5%]
Shareholding	4,480	4120	263
	[3%]	[18%]	[17%]
Private		316	2
	26,830	[1%]	[0%]
Other domestic	[17%]	792	10
		[4%]	[1%]
Total	162,033	22,111	1,518

Notes: Percentages are by column. Total industry includes all state and non-state enterprises with annual sales above 5 million yuan. Source: NBS (2000).

Table 5: Summary Statistics

Variables	Description	n	mean	s.d	min	max
vshK	value share of capital (%)	6106	17%	11%	0%	94%
vshL	value share of labor (%)	6106	8%	6%	0%	46%
vshM	value share of materials (%)	6106	58%	15%	0%	98%
vshElect	value share of electricity (%)	6106	8%	8%	0%	81%
vshNelect	value share of non-electric energy (%)	6106	9%	11%	0%	97%
pk	price of capital	6106	0.3	3.0	0.0	38.7
pl	price of labor (￥1000/person)	6106	13.0	1.8	0.2	169
pm	price of materials	6106	9.0	1.0	7.8	11.9
pele	price of electricity (￥1000/mwh)	6106	5.2	1.9	0.0	90.2
pnele	price of non-electric energy (￥1000/sce)	6106	0.6	2.5	0.0	69.1
sales cost	sales cost (￥million)	6106	855	2663	0	53100
ei	electricity intensity (normalized)	11	0.3	0.3	0	1
self_gen	% of enterprises that self generate electricity	30	18%	5%	12%	30%
scarcity	electricity ave capacity factor (by grid, year)	30	0.6	0.1	0.4	0.6

Table 6: Descriptive Regressions

Method	lnRevenue	lnqL	lnqK	lnqM	lnqElect	lnqNelect
OLS	-0.29	-0.11	-0.35*	-0.42**	-0.04	-0.55*
	(0.19)	(0.14)	(0.21)	(0.20)	(0.24)	(0.32)
	[-5%]	[-2%]	[-7%]	[-8%]	[-1%]	[-10%]
IV	-0.28	-0.15	-0.39	-0.47*	0.08	-0.68
	(0.28)	(0.20)	(0.28)	(0.28)	(0.32)	(0.42)
	[-5%]	[-3%]	[-7%]	[-9%]	[1%]	[-13%]

Notes: Clustered standard errors are reported in parentheses. Regressions include firm and industry*year fixed effects. Numbers in brackets show percent change in the natural log of revenue, labor, capital, materials, electricity and nonelectric energy given the change in our measure of scarcity from 1999 to 2004. We instrument using cooling degree days and heating degree days.

Table 7: The Effect of Electricity Reliability on Cost Functions

Key Variables of Interest	SUR	IV-SUR	Average Price	Relax CRS
ln(scarcity)	-0.1486	-0.1381	-0.1599	-0.3646**
	(0.1565)	(0.1481)	(0.1531)	(0.1566)
ln(P capital)*ln(scarcity)	0.0523***	0.0452***	0.0492***	0.0440***
	(0.0163)	(0.0162)	(0.0178)	(0.0156)
ln(wage)*ln(scarcity)	-0.0238***	-0.0223**	-0.0174**	-0.0218***
	(0.0087)	(0.0087)	(0.0088)	(0.0083)
ln(P materials)*ln(scarcity)	0.1136***	0.1300***	0.0979***	0.1091***
	(0.0286)	(0.0281)	(0.0261)	(0.0267)
ln(P electricity)*ln(scarcity)	-0.0272**	-0.0296**	-0.0171	-0.0208
	(0.0137)	(0.0137)	(0.0137)	(0.0134)
ln(P other energy)*ln(scarcity)	-0.1149***	-0.1234***	-0.1126***	-0.1105***
	(0.0168)	(0.0166)	(0.0170)	(0.0167)
Enterprise fixed effects	Yes	Yes	Yes	Yes
Industry*year fixed effects	Yes	Yes	Yes	Yes
Input price*year fixed effects	Yes	Yes	Yes	Yes
R-Squared	0.9342	0.9342	0.9398	0.3464

Table 8: The Effect of Electricity Reliability by Electricity Intensity

	Main Effects	Interacted with Electricity Intensity
ln(s)	-0.0517	0.8312
	(0.2442)	(0.5423)
ln(P capital)* ln(s)	0.0915 ***	0.2169***
	(0.0191)	(0.0296)
ln(wage)* ln(s)	-0.0351 ***	0.0288
	(0.0120)	(0.0218)
ln(P materials)* ln(s)	0.0349	-0.1146***
	(0.0289)	(0.0273)
ln(P electricity)* ln(s)	0.0254	-0.1367***
	(0.0187)	(0.0329)
ln(P other energy)* ln(s)	-0.1167 ***	0.0055
	(0.0224)	(0.0384)
Enterprise fixed effects	Yes	
Industry*year fixed effects	Yes	
Input price*year fixed effects	Yes	
R-Squared	0.9398	

Table 9: The Effect of Electricity Reliability by Industry

Industry	ln(scarcity)	ln(scarcity) × ln(P capital)	ln(scarcity) × ln(wage)	ln(scarcity) × ln(P materials)	ln(scarcity) × ln(P electricity)	ln(scarcity) × ln(P other energy)
Mining	0.39	0.23***	0.14***	0.01	-0.13***	-0.25***
	(0.56)	(0.04)	(0.02)	(0.07)	(0.03)	(0.04)
Food	-0.91	0.16**	0.02	-0.13	0.05	-0.09
	(0.95)	(0.07)	(0.04)	(0.12)	(0.06)	(0.07)
Text	0.22	0.08	-0.05	0.11	-0.05	-0.09
	(0.94)	(0.07)	(0.04)	(0.12)	(0.06)	(0.07)
Timber	-0.91	-0.03	-0.07	0.28**	0.03	-0.21***
	(1.02)	(0.08)	(0.04)	(0.14)	(0.06)	(0.08)
Petroleum	1.07	-0.06	0.05	0.24	0.09	-0.31***
	(0.94)	(0.10)	(0.06)	(0.18)	(0.09)	(0.10)
Chemical	-0.88	0.02	-0.03	0.19*	-0.03	-0.15**
	(0.85)	(0.06)	(0.03)	(0.11)	(0.05)	(0.06)
Rubber	0.53	0.08	-0.11**	0.22	-0.02	-0.16*
	(1.23)	(0.10)	(0.05)	(0.17)	(0.08)	(0.10)
Non metal	-0.28	0.06	-0.06*	0.06	-0.01	-0.06
	(0.89)	(0.06)	(0.04)	(0.11)	(0.05)	(0.07)
Metal	0.53	-0.02	-0.09**	0.28**	-0.02	-0.14**
	(0.95)	(0.07)	(0.04)	(0.12)	(0.06)	(0.07)
Machinery	-0.25	0.00	-0.03	0.07	0.02	-0.06
	(0.90)	(0.07)	(0.04)	(0.12)	(0.06)	(0.07)
Other	0.21	0.00	0.01	0.10	-0.17***	0.07
	(1.06)	(0.08)	(0.04)	(0.14)	(0.07)	(0.08)

Table 10: The Effect of Electricity Reliability by Region

Region	ln(scarcity)	ln(scarcity) × ln(P capital)	ln(scarcity) × ln(wage)	ln(scarcity) × ln(P materials)	ln(scarcity) × ln(P electricity)	ln(scarcity) × ln(P other energy)
North	-0.25	0.03	-0.19***	0.93***	-0.38***	-0.38***
	(0.57)	(0.09)	(0.06)	(0.16)	(0.07)	(0.11)
Northeast	0.67	0.11	-0.03	0.64***	-0.30***	-0.41***
	(0.80)	(0.14)	(0.08)	(0.23)	(0.11)	(0.15)
East	0.22	-0.01	-0.07	0.50**	-0.26***	-0.17
	(0.72)	(0.12)	(0.07)	(0.21)	(0.10)	(0.14)
South	-0.60	0.02	-0.07	0.38*	-0.17*	-0.17
	(0.74)	(0.13)	(0.07)	(0.21)	(0.10)	(0.14)
Southwest	-0.49	0.08	-0.06	0.30	-0.12	-0.19
	(0.80)	(0.14)	(0.08)	(0.23)	(0.11)	(0.15)

Table 11: Enterprise Decision to Self-Generate Electricity

Dependent variable:

Col. (1)-(2): an indicator of self generation;

Col. (3)-(4): fraction of electricity used that is self supplied.

	OLS	Probit	OLS	Tobit
Key Variables of Interest	(1)	(2)	(3)	(4)
ln(scarcity)	0.0157	-1.2965	0.1163**	0.1885
	(0.1275)	(2.6651)	(0.0587)	(0.4043)
Electricity Intensity* ln(scarcity)	-0.2230	-1.5249	-0.2634**	-0.8085
	(0.2832)	(5.5437)	(0.1305)	(0.8324)
ln(price of capital)	-0.0012	-0.0612	0.0008	-0.0104
	(0.0081)	(0.1479)	(0.0038)	(0.0202)
ln(price of labor)	0.0431**	1.0331***	0.0183*	0.1377***
	(0.0207)	(0.3357)	(0.0095)	(0.0506)
ln(price of materials)	1.9542***	22.4717***	1.1885***	3.3617***
	(0.4676)	(8.5794)	(0.2155)	(1.1890)
ln(price of electricity)	-0.0028	0.0717	0.0011	0.0245
	(0.0128)	(0.2647)	(0.0059)	(0.0383)
ln(price of oil)	-0.0032	-0.3469	-0.0042	-0.0392
	(0.0139)	(0.2732)	(0.0064)	(0.0396)
ln(price of other energy)	-0.0029	-0.0807	0.0068	-0.0017
	(0.0106)	(0.2038)	(0.0049)	(0.0286)
Industry*year fixed effects	Yes	Yes	Yes	Yes
Enterprise fixed effects	Yes	No	Yes	No
Ownership, region fixed effects	No	Yes	No	Yes

Note: Standard errors reported in parenthesis with significance denoted at the 1% (***), 5% (**), and 10% (*) level. Scarcity is measured by thermal utilization rate.

Table 12: Enterprise Decision to Self-Generate Electricity by Industry

		Regional Factor Prices		*Own Factor Prices*	
Industry	EI Index	Indicator Variable	Rate of Sef Gen.	Indicator Variable	Rate of Sef Gen.
Mining	0.61	0.29	0.20	0.50	0.11
		(0.39)	(0.19)	(0.44)	(0.22)
Food	0.03	0.09	0.23	0.12	0.48**
		(0.34)	(0.23)	(0.32)	(0.20)
Text	0.00	-0.11	0.03	-0.20	0.00
		(0.22)	(0.10)	(0.22)	(0.09)
Timber	0.20	-0.77*	-0.09	-0.58	-0.04
		(0.45)	(0.24)	(0.51)	(0.27)
Petroleum	0.18	0.35	-0.48	2.05	0.15
		(1.75)	(0.72)	(1.94)	(0.12)
Chemical	0.51	-0.27	-0.20***	-0.28	-0.18**
		(0.18)	(0.07)	(0.19)	(0.07)
Rubber	0.19	0.10	0.00	0.31	0.00
		(0.36)	(0.01)	(0.42)	(0.01)
Non metal	0.51	0.17	0.16**	0.21	0.18**
		(0.13)	(0.07)	(0.16)	(0.08)
Metal	0.53	-0.43	-0.11	-0.40	-0.03
		(0.29)	(0.08)	(0.32)	(0.08)
Machinery	0.07	-0.03	0.02	0.06	0.04
		(0.10)	(0.02)	(0.09)	(0.02)
Other	1.00	-0.05	0.01	-0.33	-0.02
		(0.14)	(0.02)	(0.20)	(0.03)

Notes: OLS controlling for either regional average or own input prices, as well as firm and year fixed effects.

Table 13: Enterprise Decision to Self-Generate Electricity by Region

	Indicator Variable		*Self Generation Rate*	
Region	ln(S)	ei*ln(S)	ln(S)	ei*ln(S)
North	0.09	0.16	-0.01	0.27
	(0.20)	(0.41)	(0.10)	(0.21)
Northeast	0.28	0.40	0.08*	0.01
	(0.18)	(0.34)	(0.04)	(0.08)
East	-0.06	0.33*	-0.04	0.10
	(0.08)	(0.19)	(0.03)	(0.07)
South	0.10	-0.16	0.20***	-0.20
	(0.12)	(0.26)	(0.06)	(0.13)
Southwest	0.00	0.00	0.00	-0.02
	(0.00)	(0.00)	(0.01)	(0.03)

Notes: OLS controlling for own input prices, and firm and year fixed effects.

Table 14: Effects of Electricity Scarcity on Cost, 1999-2004

	Marginal cost (million yuan)	P-value	Total effect on cost, 1999-2004 (mill. yuan)	% of sample value added, 1999-2004
Average Calculation				
Factor neutral effects	-229	0.34	-31,572	-3.39%
Factor biased effects	207	0.06	28,539	3.06%
Capital	-102		-14,062	-1.51%
Labor	-94		-12,959	-1.39%
Materials	385		53,080	5.69%
Electricity	-69		-9,513	-1.02%
Non-electric energy	88		12,132	1.30%
Overall effects	-22	0.91	-3,033	-0.33%
Enterprise-level calculation				
Factor neutral effects	-225		-23,207	-2.49%
Factor biased effects	154		18,170	1.95%
Overall effects	-70		-5,036	-0.54%

Table 15: Effects of Electricity Scarcity on Carbon Emissions, 1999-2004

	Marginal emissions (th. tons)	P-value	Total effect on emissions, 1999-2004 (th. tons)	% of total sample emissions, 1999-2004
Average Calculation				
Factor neutral effects	-117	0.06	-16,152	-1.144%
Electric power	-5	0.59	-698	-0.072%
Non-electric energy	-112	0.04	-15,454	-1.095%
Enterprise -level calculation				
Total effects	-422		-47,618	-3.373%
Electric power	-214		-25,814	-1.829%
Non-electric power	-208		-21,804	-1.545%

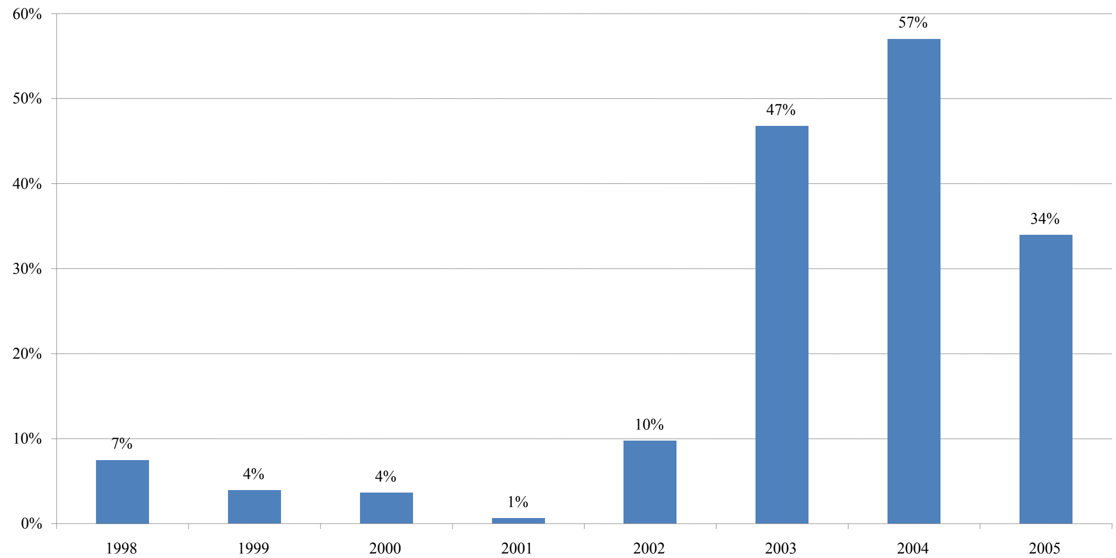

Figure 1: Influence of Brownouts on Service Reliability (%). Source: Electricity yearbook (Chen and Jia, 2005)

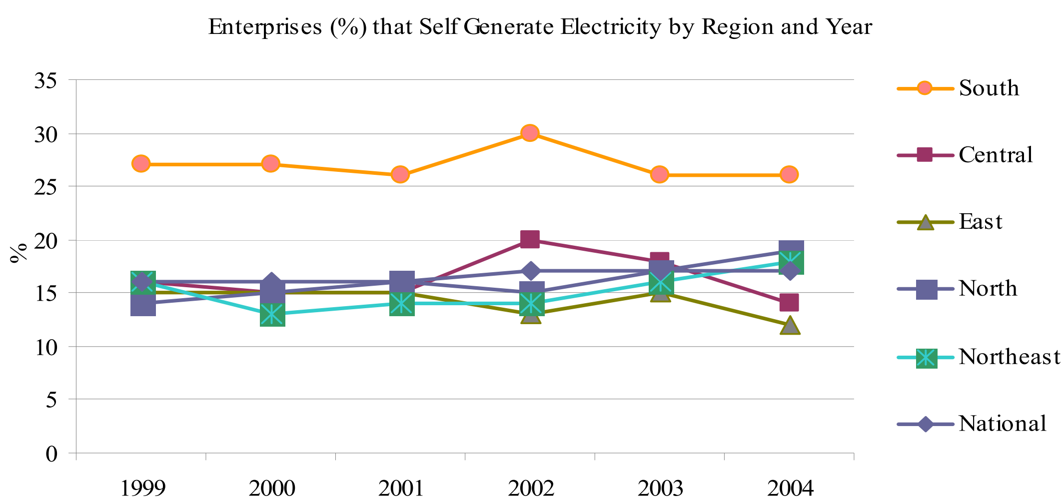

Figure 2: Percentage of Enterprises that Self-generate Electricity by Grid and Year

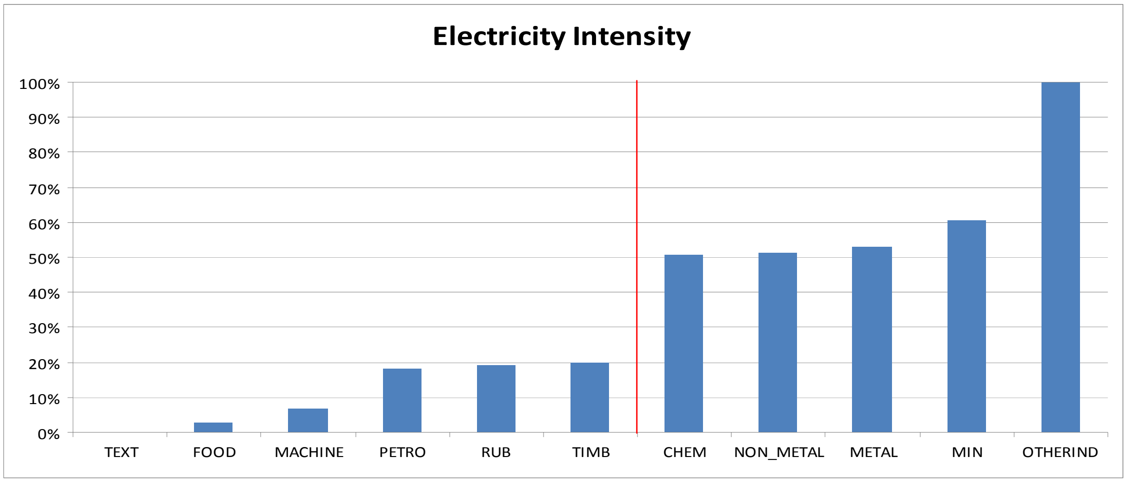

Figure 3: Electricity Intensity by Sector (normalized)

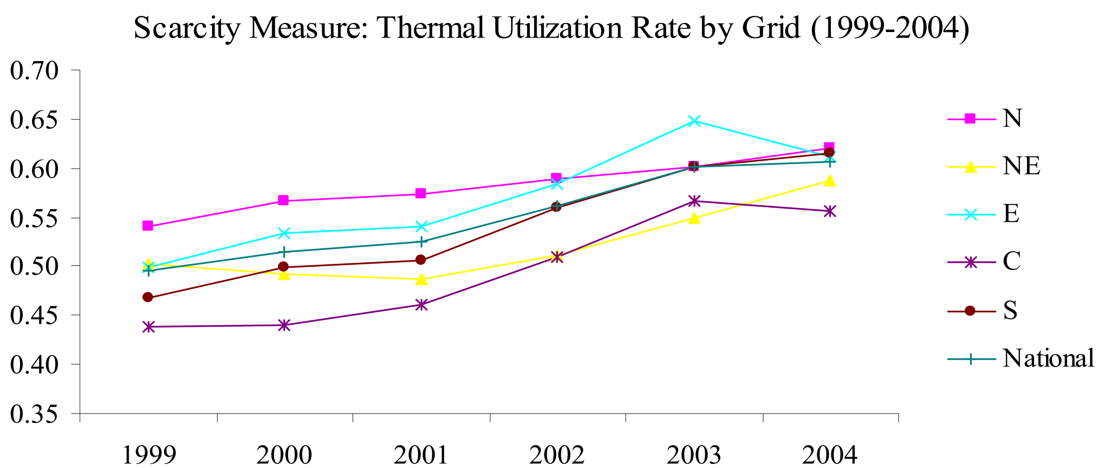

Figure 4: Thermal Utilization Rate by Grid (1999-2004)

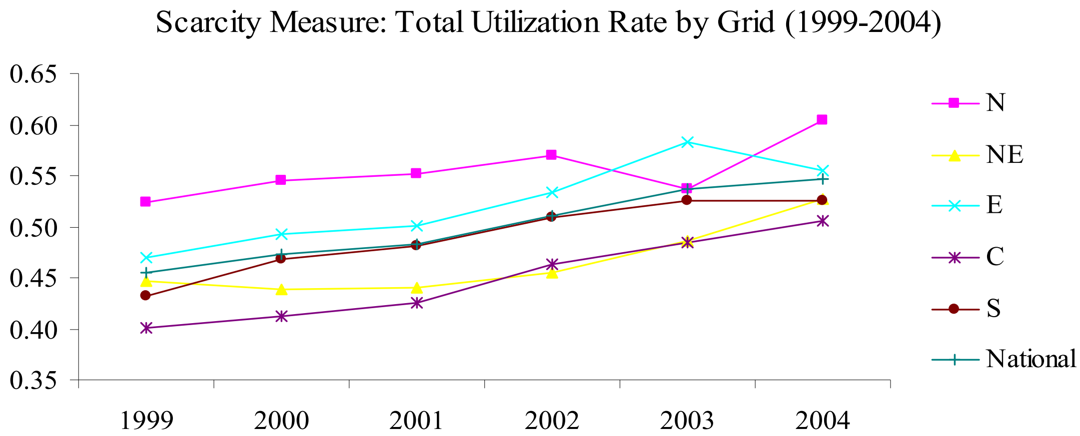

Figure 5: Total Utilization Rate by Grid (1999-2004)

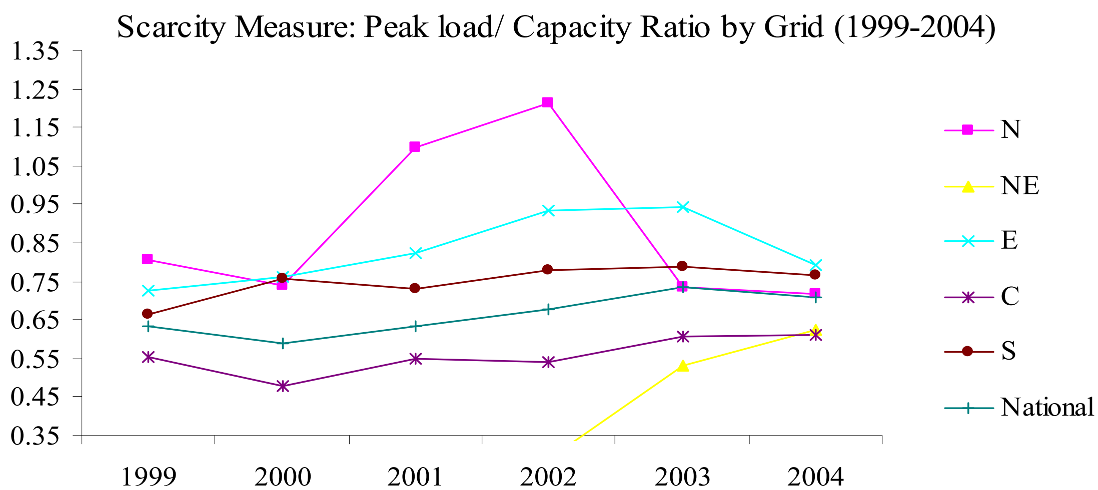

Figure 6: Peak load vs. Capacity Ratio by Grid (1999-2004)