WHEN THE LIGHTS GO OUT: POWER OUTAGE AND FIRM PERFORMANCE IN DEVELOPING COUNTRIES

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When the Lights Go Out: Power Outage and Firm Performance in Developing Countries

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Abstract

Severe power outages are widespread in developing countries and can significantly undermine firm performance. This study examines their effects using data from the World Bank Enterprise Surveys (WBES), covering 63,200 manufacturing establishments across 121 developing countries between 2006 and 2019. The results indicate that power outages have different effects on firms that generate their own electricity and those that do not. In response to greater power outages, firms with in-house electricity generating capacity produce a larger share of their own electricity, and subsequently spend more on fuel expenses, but they fail to eliminate revenue losses from power outages. Analysis using difference-in-differences estimation further shows that the adverse effects of power outages are more pronounced in energy-intensive industries regardless of in-house power generation status. This effect is also greater among smaller firms than it is for medium and large enterprises. The results remain robust when alternative specifications are estimated that use different measures of power outage and energy intensity.

Keywords: Power outage; power generation; firm performance; developing countries

1. Introduction

Manufacturing in developing countries exhibits low levels of performance in terms of metrics such as productivity, growth, and export performance (Bloom et al, 2010; Harrison et al, 2014; Bah and Fang, 2015). The sector also tends to be dominated by microenterprises, resulting in a relatively small average firm size compared with that in advanced countries (Hsieh and Olken, 2014). These patterns point to the presence of market and policy distortions that limit the growth of small firms, reduce productivity and encumber competitiveness. Previous research has documented the role of different regulatory constraints and imperfections in input and output markets[1]. A less studied but potentially important factor is the poor provision of intermediate inputs such as electricity. The World Bank's Enterprises Survey (WBES) indicates that, among 16 constraints, electricity interruption was cited as the most important constraint, topping other challenges like financial access (Figure 1). Among 63,200 manufacturing establishments, 10,670 (16.9%) rated electricity interruptions as the most binding constraint, followed by 9,850 (15.6%) that cited lack of financial access as the most pressing constraint.

Electric power outages can impair firm performance in several ways, with implications for aggregate economic outcomes. Along the extensive margin, persistent electricity outages create distortions in the business climate and increase the expected cost of doing business, discouraging potential entrepreneurs from establishing businesses in locations without a reliable supply of electricity. The resulting erosion of market confidence can also amplify uncertainties and discourage existing firms from making 'irreversible' investments in new technologies that can boost performance (Bloom et al, 2007). Along the intensive margin, electricity shortages exert an adverse impact on productivity and profit by increasing the cost of operation. The intensity of power outages is such that in some countries the vast majority of firms are forced to install independent power generators (World Bank, 2016). While self-generated electricity can fill in

[1] Researchers have investigated the role of high entry costs (Ayyagari et al, 2007; Klapper et al, 2006), excessive taxation (Biggs, 2002), and inefficient regulatory frameworks that push firms into the informal economy (Tybout, 2000). Low-income countries are also characterized by undeveloped financial markets, which could adversely affect firm performance especially in capital intensive manufacturing industries (Harrison et al, 2014; Banerjee and Duflo, 2008; Beck and Demirguc-Kunt, 2006).

electricity supply gaps during power outages, it is not likely to fully mitigate the costs of power outages as it is generally more expensive than electricity from the public grid due to increasing returns to scale (Foster and Steinbuks, 2009; Mensah, 2018). [2] Moreover, not all businesses can afford the extra costs of buying, installing, maintaining, and servicing independent power units.

Finally, frequent power outages could also reduce aggregate productivity by inhibiting the growth of small and productive firms. To the extent that coping with power outages requires costly investments for installing independent power generation units, small and medium-sized firms with limited financial resources will be more severely affected. Indeed, Allcott et al. (2016) find that variable profit losses from power outages in India are two to three times larger for small plants than for larger plants. Likewise, Alby et al (2012) find that small firms might be unable to survive in countries with significant power outages, especially in electricity-intensive sectors. Rampant power outages could thus skew the size distribution of firms towards larger firms and undermine aggregate productivity by limiting the growth and entry of productive small firms (Inklaar et al, 2017; Bloom et al, 2010; Beck et al, 2007).

Although emerging evidence suggests that power outages in developing countries expose firms to additional costs (Alby et al, 2011; Foster and Steinbuks, 2009; Arnold et al, 2008), there is limited rigorous evidence on the specific channels through which they affect firms. The few studies that look into the question either exclusively focus on one or a few countries (Allcott et al, 2014; Arnold et al, 2008) or use cross-country data that is not suited for identifying specific impact pathways (Andersen and Dalgaard, 2013). An important reason for the limited research in this area is the lack of accessible and reliable plant-level data in developing countries (Harrison et al, 2014).

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[2] Reports based on data from the WBES database reveal that 85% of firms in Lebanon and nearly 70% of firms in Djibouti own or share generators to cope with frequent power outages (World Bank, 2016). However, self-generated electricity is more expensive in many countries where the use of large, hydro sources creates high scale advantages compared to operating generators that consume expensive (and often imported) fuels (Foster and Steinbuks, 2009). The major exceptions are the countries in which fuel is heavily subsidized (Algeria, Arab Republic of Egypt, and Eritrea), where the average cost of self-generated electricity is close to the cost of the electricity from the public grid (Foster and Steinbuks, 2009).

Figure 1 about here

The objective of this research is to address the existing gap in the literature by analysing the effect of power outages on various performance metrics of manufacturing firms. The study makes a number of contributions to the literature. First, it provides robust evidence using difference-in-differences estimation, which helps us assess if power outages have a more pronounced effect on the performance of firms that operate in more energy-intensive industries. Previous research has used other identification approaches, such as fixed effects panel estimators that remove a large part of the time-invariant difference in power disruption across geographic locations. Cross-sectional studies equally fail to find instruments that vary across regions and thus focus on cross-country variation. The use of difference-in-differences estimation in this study allows us to exploit significant subnational differences in the reliability of power provision while directly accounting for geographic heterogeneities through the inclusion of city or district dummies.

Second, the study provides a more complete understanding by analysing multiple areas of performance including labour productivity, sales growth, and capacity utilization. Previous research into developing countries has relied on generic measures of performance such as average firm size across industries (Alby et al, 2012), sales volume (Cole et al, 2018), and value added (Grainger and Zhang, 2017). Considering that power outages have effects on costs, outputs, and growth prospects, simple performance measures may fail to depict a complete picture. The final contribution is that the analysis accounts for differences in independent power generation, which has a non-trivial role in moderating the relationship between power outages and performance. Self-generation has a complex relationship with performance, since firms are more likely to generate their own electricity when they are larger in size, have greater productivity, and face greater exposure to power outages. While this complex relationship makes it difficult to isolate the effect of self-generation on performance, we allow for a more flexible specification that allows the effect of power outages on performance to vary by the capacity to generate electricity in-house. Previous research into the topic has not succeeded in addressing this important source of heterogeneity due to a lack of data on the use of independent power generators.

The remaining parts of this paper are organized as follows. The next section outlines our empirical methodology, and section three introduces our data sources and variables. Section four provides the main results and some sensitivity tests, and section five concludes the paper.

2. Empirical strategy

Endogeneity is a major challenge in assessing the effect of power outages on firm performance since power outages are likely to be correlated with unobserved determinants of firm performance. The intensity of power outages could be correlated with other factors that drive firm performance, such as industry composition, prevailing economic conditions in the country, institutional quality, etc. First, power outages are likely to be endogenous to growth and business climate at a local level since administrative units that provide business-friendly services are also likely to have a more reliable power distribution network. Power outages could thus capture unobserved factors related to government quality, such as the reliability of public services and the efficiency of regulation. Second and related, power outages could reflect increased energy demand, which will be higher in high-growth, more competitive subregions. Third, the initial location decision of firms may be influenced by the quality and reliability of the electricity infrastructure. Firms with a high level of electricity dependency, for example, could choose to locate in locations with reliable electricity supply and, in the extreme case, may decide to locate close to power plants (Cole et al, 2018). Likewise, governments could also provide more reliable power services in areas where competitive firms are located. Finally, there may be measurement error in self-reported measures of power outage, which could result in a downward "attenuation bias" in regression analysis (Mensah, 2016).

Researchers have used several approaches to overcome endogeneity challenges. The first approach is including firm fixed effects, which is often followed by studies that use panel data from a single country [examples include Fisher-Vanden et al (2015) for China; Abeberese (2017) and Allcott et al (2016) for India]. Unfortunately, a panel dataset covering a broad set of developing countries is lacking, forcing researchers to use cross-sectional data. In these studies, researchers have used instrumental variable estimation to overcome endogeneity problems.

Relevant instruments include energy prices (Abeberese, 2017), variations in hydroelectric generation, and the real price of diesel (Mensah, 2016; Cole et al, 2018). These instruments, however, tend to have limited explanatory power since they are fixed across firms at a time, while power outages could vary significantly among firms located in different locations.

We use a difference-in-differences specification that exploits exogenous variations across industries and regions to overcome identification challenges. This approach allows us to test if firms in industries with greater energy intensity (PINT) suffer more when they are located in administrative regions that experience higher levels of power outage (PO). Since both power intensity and aggregate power outages are exogenous to the firm, the interaction term between the two gives an unbiased estimate of how the effect of power outage varies among industries with different levels of energy intensity. Note that in our dataset, PO is measured at the firm level, based on self-reported values of the number of times a firm experienced a power outage in a typical month. We use city/district averages for our analysis to reduce potential reliability issues in these self-reported values, which could depend on the memory and observation skills of respondents. This measure of power outage is right-skewed, so the analysis is done based on log-transformed values.

Our specification allows heterogeneous effects between firms that generate their own electricity and those that do not. In other words, the interaction term is allowed to take different coefficients between firms that generate their own electricity (SG = 1) and those that do not do so (SG = 0), where SG denotes the status of self-generation. The differential effects of power outage among firms with different energy intensity are tested as follows:

$$(1) \quad Y_{ijc} = \beta_0\left(PO_c * PINT_j | SG = 0\right) + \beta_1\left(PO_c * PINT_j | SG = 1\right) + \gamma\left(X_{ijc}\right) + \delta_j + \delta_c + \left(\varepsilon_{ijc}\right),$$

where the subscript i denotes the firm, j denotes its industry, and c indicates the city or administrative district where the firm operates. The dependent variable Y is one of the six outcome variables that will be described shortly. X is a vector of firm-specific controls, namely financial access, size dummies, age (in log-form), foreign and public ownership dummies, and a dummy indicating whether a plant is part of a multi-unit firm. δ_j and δ_c are vectors of dummy variables indicating the firm's industry and city or administrative district, respectively. As our sample is international, the city dummies also capture cross-country variations in institutional quality and other macroeconomic conditions. Where the same city has been covered in multiple years, δ_c also varies over those years to reflect that the subsamples come from repeated cross-sections from different years. Finally, ε is the error term of the regression model.

Equation (1) is the standard non-experimental difference-in-differences approach pioneered by Rajan and Zingales (1998), who studied how the growth of financially dependent industries suffered more from poor financial development. In our case, this specification allows us to test if the performance of high-energy-intensity firms is more severely affected in cities that experience greater electric power disruption. This specification reduces omitted variable bias and other misspecification problems by controlling for country, district, and industry dummies to capture institutional and structural heterogeneity across countries. The difference-in-differences approach is highly robust as it relies on exogenous structural variations across industries in terms of power intensity to capture the differential effects of power outage among firms.

The use of city-level power outage within cities *(PO_c)* is expected to limit measurement error relative to firm-level responses to power outage. Power intensity ($PINT_j$) measures technology-related structural differences in energy demand across industries and is taken from external data sources. As is typical in the literature (Rajan and Zingales, 1998), we use energy usage by US industries as a benchmark of energy intensity. As the interaction term is a product of an industry-level measure (PINT) and a city-level measure (PO), it varies both across cities and industries, allowing us to include city and industry dummies. The sign and relative magnitude of these two coefficients will depend on the outcome variable. For measures of firm performance such as labour productivity and growth, we expect the effect of power outage to be more pronounced among firms in energy-intensive industries, so that the coefficients of the interaction term, β_0 and β_1, will be negative and significant. In these regressions, we also expect that non-generating firms will suffer more from power outages; therefore $\beta_0 < \beta_1$. For different coping mechanisms, the sign of the coefficients for the interaction term, and their relative magnitude, will depend on the nature of the outcome variable in consideration.

Finally, we extend Equation (1) by allowing the interaction term between PO and PINT to vary across firms with different size groups (S_g) to test if the effects of power outages vary across firms of different size classes. Size dummies are interacted with both for the main and interaction effects of power outage:

$$(2)\ Y_{ijc} = \beta_{g,0} \sum \left(PO_c * PINT_j * S_{g,ijc} | SG = 0\right) + \beta_{g,1} \sum \left(PO_c * PINT_j * S_{g,ijc} | SG = 1\right) + \theta_{g,0} \sum \left(PO_c * S_{g,ijc} | SG = 0\right) + \theta_{g,1} \sum \left(PO_c * S_{g,ijc} | SG = 1\right) + \gamma\left(X_{ijrc}\right) + \delta_j + \delta_c + \left(\varepsilon_{ijc}\right),$$

where S_g is a size class that indicates whether a firm is small, medium, or large. The interaction term coefficients $\beta_{g,0}$ and $\beta_{g,1}$ are now indexed with size groups, g, and will be separately estimated for small, medium, and large firms. The coefficients of the main effect of power outage, $\theta_{g,0}$, are likewise allowed to vary across size groups. Both the main and interaction effects of power outage are allowed to vary across firms that generate their own electricity (SG = 1) and those that do not (SG = 0).

3. Data and measurement

3.1 Data sources

The analysis is conducted using the 2019 release of the World Bank's Enterprise Surveys (WBES) database, which is based on a standardized survey that collects rich information on firm performance and managerial perceptions of business environments. The WBES collected data from approximately 135,000 establishments across 139 countries between 2006 and 2019. This study draws on a subset of the database comprising manufacturing firms only.[3] The major strength of WBES is that the data are collected systematically using standardized survey instruments. Designed to enhance the availability of good-quality data in developing countries,

[3] More information about WBES database can be found at: www.enterprisesurveys.org. We restrict the sample to the 2006–2019 period to avoid the methodological complications introduced by COVID-19, during which policy responses caused endogenous production disruptions that varied systematically across cities and countries.

the WBES database covers the great majority of developing countries and is unique for its comparability and extensive country coverage.

To facilitate comparability across countries, the surveys exclude micro-enterprises, small firms with less than five employees, and wholly state-owned enterprises. To ensure representative coverage for the formal economy of a given country, WBES employs a stratified sampling procedure based on industry groups, firm size, and geographic location. Sampling starts by specifying the number of industry groups to be covered across each major sector (services, manufacturing, and non-agriculture primary activities). For manufacturing, industry grouping is based on two-digit ISIC classification.

The number of industry groups to be covered in each country is determined according to the size of the total economy, which is taken as a proxy for the universe of firms. Once the number of industries to be covered is decided, the largest industry groups in the economy, in terms of contribution to output and employment, are selected. In the second stage, a sampling equation is used to determine a representative sample size per industry group. The sample size is chosen to achieve representativeness for the proportion of plants and the average sales in the industry. Finally, further stratification is made based on firm size and geographical location to select the plants that are covered by the survey.

We used a pooled sample of the dataset covering the years 2006 to 2019. The sample includes 63,200 establishments across 121 countries (or 207 country-years), although the actual sample size is much smaller for some outcome variables. We chose to use the pooled sample rather than removing repeated observations to increase sample size, especially since our measure of power outage is missing for a large number of firms. As indicated in the methodology section, dummy variables indicating the year of data collection within each city are included to capture any temporal changes.

3.2 Measurement of variables

A) Dependent variables. The relationship between power outages and firm performance can depend on the chosen performance metric, in part because firms develop different strategies to cope with power outages. For example, Allcott et al (2016) report that Indian firms experienced negligible productivity reduction in spite of losing 5-10% of their revenues due to power outages, because plants substituted inputs or simply stored inputs during outages. Fisher-Vanden et al (2015) find that Chinese firms actually achieved small total factor productivity improvements in spite of a 13% increase in unit cost due to power shortage. One form of substitution involves outsourcing energy-intensive intermediate inputs, thus substituting energy costs with materials costs (Fisher-Vanden et al, 2015). Abeberese (2017) also finds that Indian firms experiencing high electricity prices switched to less electricity-intensive production processes. Both Abeberese (2017) and Allcott et al (2016) find that revenue falls due to power outages were not accompanied by changes in employment, pointing to the rigidities in adjusting labour inputs.

To help pin down the specific routes through which power outages affect firms, we assess their effect both on coping mechanisms and multiple measures of performance. We examine the relationship between power outages and coping mechanisms, including the share of electricity generated in-house, fuel costs, and the number of active operating hours. We also analyse the effects of power outages on firm performance metrics, focusing on capacity utilization, sales growth, and labour productivity.

Coping mechanisms

1. *Self-generation of electricity* - the percentage share of electricity that is generated in-house.
2. *Fuel costs* – measures the costs of fuel as a percentage share of labour, energy and materials costs.
3. *Active hours* – the average number of hours the firm operated in a typical week.

Firm performance

4. *Capacity utilization* – output produced as a proportion of the maximum output possible in a fiscal year.
5. *Sales growth* - calculated from sales revenue figures in the current fiscal year, and three years ago (both figures are reported within each survey).

6. *Labour productivity* – calculated as total sales revenue per unit of labour cost. Unit labour cost rather than labour units is used to better capture quality differences in labour inputs and also avoid the challenge of converting part-time employment into full-time equivalent.

B) Power outage. We measure power outage using self-reported values of the frequency of electricity interruptions in a typical month. The WBES provides firm-level responses of power outage, indicating the number of incidents of power interruption in a typical month (PO), but we use city/district averages in our main specifications for many reasons. First, self-reported values of power outage experiences could lack reliability, since they will depend on the memory and observation skills of respondents. Moreover, there is a likelihood of subjectivity bias since firms that face strong market demand or competition, and firms without in-house generation capacity, may have stronger perceptions, and thus memory, of the incidence of power outages. District averages of power outages help cancel out these measurement differences, while also reducing data loss from missing values at the firm level. For robustness, we also report results based on an alternative measure of power outage that captures the duration of typical power outages (POD). This measure is calculated by multiplying the average frequency of monthly interruptions in a city/district by the average length of these interruptions in hours. Our baseline analysis relies on the frequency rather than a duration-based measure, as the latter is more likely to be measured with error (for example, respondents might have difficulty remembering the 'typical' duration of outages, especially if the outages exhibit variability in their duration). Finally, the WBES dataset includes information on firms' use of independent power generators, which we draw on to compare the effects of power outages between firms that own generators and those that do not.

C) Energy intensity. Since developing countries in our dataset are beset by power outages, we rely on parameters from the relatively less distorted U.S. economy to get benchmark values of energy intensity (for similar approaches in other contexts, see Hsieh and Klenow, 2009; Inklaar et al, 2017). Our baseline analysis is based on fuel consumption per person in billions of British Thermal Units (BTUs) among US industries. Energy consumption per person is our preferred measure because, as a physical measure, it is not tainted by energy prices, which tend to vary significantly across countries but also across firms in different sectors and size categories (Davis et al, 2013). Data for 2014 at the 2-digit-level ISIC industries are taken from the website of the US Energy Information Administration Agency (EIA). The figures are generated by the EIA based on the Manufacturing Energy Consumption Survey, which is a nationally representative survey of more than 15,000 enterprises. The survey collects information on the stock of U.S. manufacturing establishments, their energy-related building characteristics, and their energy consumption and expenditures.

We expect that these values reflect the underlying technological characteristics of each industry and their respective energy demand. Nonetheless, we check the robustness of the results using two more alternative measures of power intensity. The first alternative comes from a different data source, namely the NBER-CES Manufacturing Industry Database of the US manufacturing sector. This database provides annual industry-level data from 1958-2011 on output, employment, labour, energy and other input costs based on the US Annual Survey of Manufactures and Census of Manufactures (the original documentation provided by Bartelsman and Gray, 1996). We calculated energy intensity using the percentage share of energy costs in total sales shipments at the industry level and used average values over the most recent years in the dataset (2006-2011). While this measure could capture price differences as it is not measured in physical units, it has the advantage of being more reliable as it is based on census data.

As a second alternative to our baseline indicator, we use a measure of energy consumption in BTUs per dollar of sales shipment from the EIA dataset (the same data source as the baseline indicator). This alternative measure is used to address the potential concern that energy consumption per employment might reflect potential labour intensity variations between US industries. The energy intensity values from these alternative sources are given in Table A2 and indicate broad consistency among the measures across industries.

3.3 Descriptive statistics

Table 1 presents the descriptive statistics for the key variables in our analysis. It is important to note the significant variation in the number of observations across the variables. Among the outcome variables, the number of active hours and capacity utilization are the most widely available, while electricity self-generation is the least widely available. The latter is because only 37% of the observations self-generate electricity, which is apparent from the average value of the "self-generation dummy" (see Table A1 in the Appendix). Among firms that generate their own electricity, the share of self-generation constitutes 25.5% of total energy consumption, which is a significant amount. These values vary notably across countries, ranging from Estonia (2009 & 2013), Slovenia (2009), and Bulgaria (2013), where self-generation makes up less than 1% of electricity consumption, to countries such as Liberia (2017), Chad (2009), Afghanistan (2008), Guinea Bissau (2006), and Lao PDR (2016), where more than 65% of the electricity is self-generated.

Firms report an average of almost 14 power outages per month, suggesting that electricity interruption occurs every other day. The frequency of power outages again varies notably across countries, from less than once every two months in the Philippines (2015), China (2012), and Peru (2006), to more than 60 times per month in Yemen (2010), Kosovo (2009), Bangladesh (2007 & 2013), and Pakistan (2013). Firm-level responses for power outages are available for less than 40,000 observations, leading to significant data loss. As indicated earlier, we use city averages of power outages to mitigate this loss of data and also alleviate potential measurement error in firm-level responses.

Table A1 in the Appendix provides additional descriptive statistics for the control variables. On average, firms finance about 15% of their working capital expenses through bank loans. Small firms (with less than 20 employees) constitute 40% of the sample, whereas large firms (with greater than 100 employees) make up 24% of the sample, the remaining 36% being medium-sized firms. The average firm age is 28.5 years, whereas establishments that are part of multi-plant firms make up 16% of the sample. Only 1% of the observations are partially state-owned, which reflects the focus of the WBES dataset on private enterprises. Finally, about 11% of the sample is composed of foreign-owned firms with at least a 10% foreign stake.

Table 1 about here

Table 2 provides the correlation coefficients between our eight measures of firm performance and our measures of power outage. Labour productivity, sales growth, the number of active hours, and capacity utilization are all positively correlated with each other. Energy costs are negatively correlated with all of the above except with active operating hours, with which it has a positive correlation. This confirms that the most productive firms grow faster and have better capacity utilization but also have lower energy costs. Electricity self-generation (%) is also positively correlated with fuel costs (%) and labour productivity but negatively correlated with the remaining outcome variables.

The correlations between performance measures and the other variables are rather mixed. Sales growth is negatively correlated with power outage and losses from power outage, but has an insignificant correlation with the probability of operating a generator. The other performance variables are positively correlated both with power outages and with the probability of self-generating electricity. The correlations between performance measures and power outage are mostly in line with theoretical expectations.

Table 2 about here

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4. Results

4.1 Firm heterogeneity in self-generation of electricity

Before proceeding with our main results, we first offer some prima facie evidence on the presence of firm heterogeneity related to independent power generation and firm size. Table 1 provides descriptive statistics of key variables in our regression. The last four columns of the Table also report regression coefficients that indicate the effect of power outages on different coping mechanisms and metrics of performance. In these regressions, the direct effect of power outage

(PO) on the outcome variables is tested while controlling for the full set of control variables, city dummies, and industry dummies that are indicated in Equation (1). The regressions are conducted using power outage measures at the firm level, while including city/district dummies, hence exploiting subnational variations to identify the direct effect of power outages.

To account for the potentially heterogeneous effects of power outages on generating and non-generating firms, the regressions allow separate coefficients for the two groups of firms, just in line with Equation (1). The last set of columns reports the effect of power outages on the coping mechanisms and outcome metrics of generating and non-generating firms. From the first row, we observe that power outages lead to a significantly greater share of in-house electricity generation among self-generating firms (coefficient = 3.03). Consequently, power outages have a positive and significant effect on fuel costs among generating firms (coefficient = 0.25), while this effect is insignificant among non-generating firms. On the other hand, the third row shows that power outages lead to significantly longer operational hours only among non-generating firms (coefficient = 1.34). This could be because the factory floor remains idle waiting for the return of electricity, or because disruptions in the production line create additional non-production activities that keep the plant open longer. Among the outcome variables, however, the effects are significantly different across the two groups only for capacity utilization, which is significantly lower among non-generating firms (coefficient = -0.78).

These results, for the most part, confirm that firms that generate their own electricity respond differently from firms that do not, justifying our approach for a distinct treatment of these two groups. Power outages increase in-house electricity generation, and consequently fuel costs, among self-generating firms while increasing operational hours among non-generating firms.

Figure 2 about here

Figure 2 further reveals that size is an important part of this story. Larg firms are twice as likely as smaller firms to generate their own electricity, pointing to the importance of scale for installing independent power generation units. However, the share of electricity generated independently is lower among large firms by about a third, also indicating that the variable costs of fuel could erode this scale advantage among large firms. In our subsequent analysis, therefore, we address the potential heterogeneous effects of power outages between small, medium and large firms.

4.2 Heterogeneous effects on energy-intensive industries

This subsection presents the results for the difference-in-differences specification introduced in Equation (1). By comparing the differential effect of power outages among industries with varying levels of energy demand, the analysis reveals the specific mechanism through which power outages create uneven effects across firms. In these regressions, the average of power outage at city/district-level is interacted with our industry-level measures of energy intensity that were taken from the US data. The interaction terms thus tell us whether the effect of power outages on performance is greater among firms in energy-intensive industries.

Table 3 about here

Table 3 reports the regression results where an interaction term between power outage and the benchmark energy intensity (energy consumption in billions of BTUs per employee at industry level) is included. As indicated in Equation (1), the coefficients of the interaction term are allowed to vary between firms that generate their own electricity and those that do not. The first regression, which is estimated on the subsample of firms with independent power generation, reveals that power outages lead to significantly greater in-house generation of electricity in industries with greater energy intensity. The left panel of Figure 3 reports the marginal effect of power outages on in-house generation of electricity, which is positive and significant, and increasing with the level of energy intensity. Regression 2 shows that this effect does not translate into greater fuel costs – neither among generating nor among non-generating firms. The marginal effects on fuel costs, reported in the right panel of Figure 3, are likewise insignificant at all levels of power intensity both for generating and non-generating firms.

Regression (3) shows that the interaction term between power outage and energy intensity is negative and significant for active operating hours, but only among non-generating firms. This result is also apparent from the marginal effects in the left panel of Figure 4, where only the 95%

confidence band of the blue line (for non-generating firms) is below zero. Within this group of firms, therefore, power outages reduce the operational time of energy-intensive firms, potentially leading to reduced performance. For generating firms, on the other hand, the marginal effect does not vary significantly with energy intensity, apparently due to their ability to maintain normal working hours through in-house electricity generation, as shown in regression (1). For non-generating firms, the interaction term is also negative and weakly significant for capacity utilization, confirming that reduced hours lead to capacity reduction among energy-intensive firms in this group. However, the upper 95% confidence bands of the marginal effects in the right panel of Figure 4 cross zero, reflecting the weak significance of the interaction term.

The regressions reveal that the effect of power outages on sales growth and labour productivity is negative and significant among industries with higher levels of energy intensity. This effect is of comparable magnitude among firms that generate their own electricity and among those that do not. This implies that power outages undermine the performance of energy-intensive firms regardless of generating capacity. Self-generating, energy-intensive firms suffer from lower growth and productivity in spite of coping mechanisms in the form of greater in-house electricity generation, indicating the inefficiency of relying on self-generated electricity in this subsample of firms. Non-generating, energy-intensive firms, on the other hand, suffer from lower growth and productivity apparently due to reduced working hours and capacity utilization.

Figure 3 – Figure 5 about here

Figure 5 further illustrates how the marginal effects of power outages further erode the productivity and sales growth of energy-intensive firms. A one percent increase in power outages reduces sales growth by 0.10 percentage points in the food and beverages industry, where energy consumption per employee is 0.8 billion BTUs. The marginal effect of an equivalent level of power outages is five times larger, at 0.54 percentage points, in the basic metals industry, where energy consumption per employee is 4.3 billion BTUs. The negative marginal effect of power outages on labour productivity likewise increases steadily with energy intensity. These results confirm that, although power outages have a significant negative effect on performance overall, their impact is greater by a large magnitude among energy-intensive industries.

4.3 Heterogeneous effects across size groups

This subsection reports the regression results for Equation (2), where interactions with size dummies are included to test if power outages have a disproportionate effect on smaller firms. Power outages could affect small and large firms differently, for example if the total costs of owning and operating an independent power generation unit vary non-linearly with firm size. For small firms, Foster and Steinbuks (2009) report that acquiring and operating an independent power generation unit imposes relatively low fixed costs but higher variable costs. Among larger firms, on the other hand, acquiring high-powered generators increases fixed and variable costs. Likewise, Alby et al (2012) find that self-generation depends on electricity intensity, firm size, and credit access.

Prior evidence hence seems to indicate potentially uneven effects of power outages among firms of different size classes. To test for this possibility, we report estimates of regressions that include a four-way interaction between power outage, energy intensity, self-generation status, and firm size dummies. Among these four variables, power outage and energy intensity are continuous, while firm size and self-generation status are categorical variables with three and two groups, respectively. As shown in Equation (2), we allow the interaction between the two continuous variables to vary between the six groups of firms that vary by size and self-generation status. These results are reported in Table 4, where the first rows present the coefficients of the interaction terms between power outage and energy intensity for the six firm groups.

Table 4 about here

The results reveal that the effects of power outages vary among firms with different size groups and self-generation status for many outcome variables. Regression (1) shows that the extent to which power outages lead to greater in-house generation among energy-intensive industries increases with size. The interaction term between power outage and energy intensity is insignificant for small firms, only weakly significant for medium firms, and highly significant among large firms.

The interaction terms are separately estimated to assess the sign and significance for each group of firms; an equivalent estimation approach is leaving out one of the firm groups to allow comparison of coefficients for the remaining groups against those of the excluded base group. A more convenient approach for assessing marginal effects in estimations involving more than two interacting variables is evaluating *predictive margins.* Figures 6-8 report the predictive margin for firms of different size groups and power generation status to assess the adjusted treatment mean of the outcome variables for changes in size and generation status. The figures report predictive margins based on the results of Table 4 and are computed by letting all observations take the values of the specified size and self-generation status, while allowing for different covariate distributions in the groups. The average predictive margins and their 95% confidence interval bands are plotted in Figures 6-8 to allow testing if the predicted group means are statistically different from the overall sample mean. For example, the left panel of Figure 6 shows that the average share of in-house generated electricity is 25.5%, while the predictive margins indicate that the predicted value increases with size. However, the predictive margins of all three size groups are not statistically different from the sample average, suggesting minor differences between them. This reveals that, keeping other things constant, changes in size groups do not lead to highly different predictions in the level of in-house generated electricity.

Turning to Table 4, regression (2) reveals some differences in the coefficients of the interaction terms across firm groups. Among small and self-generating firms, the effect of power outage on fuel consumption seems to increase with energy intensity, while the reverse is true for medium-sized, non-generating firms. Since fuel costs should reflect the cost of powering in-house generators, we would have expected that fuel costs would increase with energy intensity among generating firms. A potential explanation for this counterintuitive result is that fuel has multiple uses, including transpiration. The left panel of Figure 6 reports the predictive margins of size and generating status on fuel consumption. Comparison of average predictive margins across groups allows us to assess predicted differences in fuel cost after controlling for other sources of variation in energy intensity and power outage (as indicated earlier, all independent and control variables are kept at the observed level for each firm, while only size and self-generation status are allowed to vary).

The Figure reveals that fuel costs fall with size regardless of generation status, pointing to notable differences in scale efficiency. This also indicates the need to compare like with like in assessing the effect of power outages. Across all size groups, fuel costs are higher among generating than non-generating firms, and these are statistically significant (i.e., the confidence interval bands do not touch each other). These results confirm that power outages lead to greater substitution of fuel for electricity among generating firms.

Regression (3) shows that the interaction between power outage and energy intensity is negative and significant for all size groups of firms without independent power generation capacity. In other words, the marginal effect of power outages on active operating hours is negative and increases with energy intensity among non-generating firms. This confirms that energy-intensive firms with internal generation capacity rely on in-house generation to reduce the number of hours they stay idle. The left panel of Figure 7, however, reveals that size is also an important predictor of operating hours: operating hours increase steeply with size. For small and medium firms, self-generation significantly boosts operating hours, suggesting that it helps them overcome power outages. Self-generation does not improve working hours for large firms, which is apparent from the overlapping spikes indicating 95% confidence intervals. This result could be either because large firms already work long hours and hence do not use self-generated electricity to extend their operating time, or because they do not find it affordable to use in-house generated electricity. Alternatively, it could be because large firms are located in districts that are less affected by power outages. Average descriptive statistics, however, do not appear to vary sufficiently to warrant such a major difference among size groups. The average response of frequency of power interruptions was 17.6 times per month for small firms, while medium and large firms reported an average interruption of about 16 times per month.

Does the reduction in working hours among energy-intensive firms that do not generate their own electricity lead to worse firm performance? Regression (4) helps answer this question by evaluating capacity utilization, which is a rough measure of performance. The interaction between energy intensity and power outage is significant only for small, non-generating firms. The size of the coefficient is negative as expected and indicates that power outages reduce capacity utilisation among energy-intensive, small firms – apparently because they work for shorter hours. For medium and large non-generating firms, the reduction in working hours that increases with energy intensity does not appear to translate into a fall in capacity utilisation. The predictive margins of capacity utilisation (right panel of Figure 7) give additional insights. Just like active working hours, the predicted capacity utilisation steadily increases with size regardless of generating status. Among small firms, and to a degree among medium firms, however, independent power generation boosts capacity utilisation. Self-generation is hence more important for improving active operating hours and capacity utilization among smaller firms than among larger firms.

Likewise, regression (5) for sales growth shows that the interaction term is negative and significant only for non-generating, small firms. This result shows that small, energy-intensive firms without in-house generation capacity are perhaps the most affected by power outages. The predictive margins for sales growth, reported in Figure 8, confirm that small non-generating firms have low predicted values of sales growth, which is significantly lower than the sample average. Among small firms, in-house generation of electricity improves sales growth by a small, but not significant margin. Once again, the figure reveals the relative growth advantage of large firms, which appears to hold regardless of the capacity for in-house electricity generation.

The results for labour productivity in the last regression show that the interaction between power outage and energy intensity is negative and significant for all groups except for medium and large generating firms. For all other firms, therefore, the effect of power outage on labour productivity increases significantly with energy intensity. Figure 8 reveals that, for all size groups, the predicted level of labour productivity is much greater for generating firms than for non-generating firms. The reason why self-generation boosts productivity but not sales growth is potentially because sales growth captures a dynamic process of expansion along the extensive margin, which is affected by a number of other contingencies (e.g., investment or market entry).

In sum, these results reveal that self-generation allows firms to increase their active operating hours and boost their performance, although the extent of this performance improvement depends on firm size. By most measures, small firms with the capacity to generate their own electricity seem to succeed in boosting their performance by a larger magnitude than large firms. Small, energy-intensive firms without in-house generation capacity appear to suffer the most from power outages.

Figure 7 & Figure 8 about here

4.4 Robustness tests

This section presents three sets of sensitivity tests for the baseline results. The first tests adopt alternative measures of power intensity, while the next two address measurement and endogeneity issues with power outage.

A. Alternative measures of energy intensity

The reliability of the interaction-effect estimates presented in the previous subsection could depend on the way energy intensity is measured, which calls for sensitivity tests using alternative measures of energy intensity. Our difference-in-differences analysis uses benchmark energy intensity data from the US. To avoid capturing differences in energy consumption patterns related to market forces that are unique to the US, such as price levels, we have measured energy intensity in physical units. Nonetheless, these measures could suffer from measurement error if there are mismatches in industry aggregation between the USA and other countries.

Therefore, we conduct sensitivity tests using two additional benchmarks for energy intensity, as described in the variable measurement section. The first is based on the share of energy costs in total sales shipments (PINT2) measured at the 2-digit ISIC industry level, taken from the NBER-CES Manufacturing Industry Database. The second measure of energy intensity is taken from the same data source as the baseline measure and is based on sectoral energy consumption in thousands of BTUs per dollar of sales shipment (PINT3). This alternative measure is thus a compromise between purely physical and monetary measures.

Table A3 and Table A4 in the Appendix report the difference-in-differences estimates based on these two alternative measures of energy intensity (PINT2 and PINT3, respectively). The top panels of these tables report the coefficients of the interaction terms for self-generating and non-generating firms based on Equation (1), while the bottom panels do the same based on Equation (2). Interestingly, both panels of Table A3 mirror the baseline results reported in Tables 3 & 4. The interaction between power outage and energy intensity is not associated with fuel usage across both firm groups, but has a significant, positive effect on the share of home-generated electricity among self-generating firms. For active operational hours, both alternative measures of energy intensity indicate a significant and negative effect both for self-generating and non-self-generating firms. These show that power outages have a greater effect of reducing active operating hours among energy-intensive industries regardless of self-generation. Interestingly, these effects are greater among self-generating firms; in other words, power outages tend to reduce the operating hours of self-generating firms that are more energy intensive, relative to other self-generating firms that are not energy intensive. This points to potential costs of running independent power generation, which limit its ability to fully substitute for the grid among energy-intensive firms.

For labour productivity, both alternative measures lead to similar effects as the baseline results: power outages appear to have a greater effect of reducing labour productivity in energy-intensive industries, regardless of self-generation. Like the baseline results, the magnitude of these effects seems to be slightly higher for non-generating firms. For sales growth and capacity utilization, the alternative measures of energy intensity fail to identify significant differences in the effects of power outages across levels of energy intensity.

B. Alternative measures of power outage

Table A5 in the Appendix reports additional sensitivity tests using the alternative duration-based measure of power outages that is calculated by multiplying the frequency of monthly interruptions by the average length, in hours, of the interruptions. Except for some differences, these results are comparable to the baseline results. Longer duration of power outages, for example, appears to lead to greater in-house generation among medium and large firms in energy-intensive industries. This again suggests that constraints in generating capacity become more binding among energy-intensive sectors. Finally, Table A5 suggests that longer power outages have a greater effect in reducing active hours in energy intensive industries regardless of in-house power generating capacity. In contrast, the duration of power outages does not appear to produce systematic performance differences in sales growth between energy-intensive and non-energy-intensive firms.

C. Instrumenting power outage

The final robustness test looks into the potential endogeneity of power outages. We have taken several precautionary measures to address potential endogeneity and measurement problems, as indicated in our empirical strategy section. Our difference-in-differences specification allows the inclusion of city/district dummies, allowing us to account for potential regional differences related to power outages that also influence firm performance.

Given its centrality in our analysis, it is nonetheless important to check the potential endogeneity of our measure of power outage. Previous researchers have used various aggregate variables as instruments for power outage. For example, Abeberese (2017) uses the price of coal as an instrument for electricity prices, while Mensah (2016) and Cole et al (2018) respectively use variations in hydro-electric generation and the real price of diesel as instruments for power outage. These instruments, however, are fixed across firms at a time, and fail to explain the major spatial variation in power outages.

In line with Cole et al (2018), who used water availability to instrument hydropower generation, we use an indicator of water shortages from the same survey dataset to instrument power outages. The WBES includes a question that asks firms how often they experienced water shortages in the same fiscal year. Since hydropower is the most important source of energy in most developing countries covered in our dataset (Cole et al, 2018), drought spells that cause water shortages are likely to predict hydropower generation, and subsequently power outages related to energy supply deficits. Allcott et al (2016) have used a similar logic to instrument power shortages using reservoir water inflows, conditioning on average rainfall. In our analysis, we consider a categorical variable with four classes that identifies the degree of water shortage (using the number of interruption incidents per month), conditioning on institutional quality. The advantage of this measure is that it is sourced from the same firms and thus reflects power generation capacity in the same geographic vicinities where we also measure power outages.

The first stage estimation relates this set of instruments to power outage levels reported by firms. The estimates are reported in Table A6 and confirm that firms that experienced more frequent water shortages also reported more frequent power outages, conditioning on institutional quality. The relationship seems to be contingent on self-generation, but the improvement in predictive accuracy is marginal, so we use the simple estimation in regression (1) to predict power outages. The predicted values are converted to levels and then averaged across cities, before being used for estimating equations (1) & (2). This separate estimation of the first and second stages has some efficiency disadvantages, but it allows us to exploit richer sub-regional variations in water availability to predict power outages. The difference-in-differences results using the predicted values of power outages are reported in Table A7, and for the most part confirm the baseline results. While not entirely foolproof, the similarity between these results and the baseline results should strengthen confidence in the robustness of the relationships.

5. Conclusion

This study has used rich survey data of 63,200 manufacturing establishments from 121 developing economies to assess the effects of power outages on firm performance. The analysis covered important performance metrics such as sales growth, labour productivity, and capacity utilization, and coping mechanisms related to active operating hours, fuel costs, and the degree of independent electric power generation. The analysis is conducted using a number of cross-sectional estimation methods with different strengths and limitations.

The main part of our analysis uses a robust, difference-in-differences specification to assess how power outages cause uneven effects on performance among firms with different levels of energy intensity. This approach exploits exogenous differences in power outages across cities and technological differences across industries in energy intensity to assess how power outages affect firms unevenly. In departure from past research, our analysis explicitly addresses firm heterogeneity in terms of capacity to generate electricity in-house and firm size. We control for city and industry fixed effects to overcome potential endogeneity problems related to omitted variables and simultaneity. The last part of our analysis further addresses the potential role of size by allowing the effects of power outages to vary across firm-size groups.

The results reveal the heterogeneous effects of power outages on firm performance and the presence of diverse coping strategies. Firms respond to power outages by increasing the amount of electricity generated in-house but often do not successfully mitigate the negative consequences. On average, non-generating firms respond by increasing their operating hours, but the reverse occurs among energy-intensive firms. Power outages lead to significantly greater reductions in sales growth and productivity among energy-intensive firms regardless of their capacity to self-generate power. Finally, small firms suffer more from power outages by most measures, but the ability to generate their own electricity helps them mitigate the adverse effects of power outages. These results point to the importance of examining different coping strategies and explicitly addressing heterogeneous firm responses to better understand how firms respond to power outages.

These findings have important policy implications. They underscore the productivity and growth benefits of a reliable electricity supply, which reduces firms' reliance on costly in-house power generation. Given that private power generation is both expensive and insufficient to offset the productivity and revenue losses associated with power disruptions, policymakers should prioritize improving the reliability and predictability of electricity supply. This requires sustained investment in electricity generation, transmission, and distribution infrastructure to reduce the frequency and duration of outages, which disproportionately affect small firms and energy-intensive industries. The findings also point to the need for targeted policy interventions to alleviate the particularly high costs of power disruptions in energy-intensive sectors, where improvements in electricity reliability are likely to yield the greatest productivity and growth gains.

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Tables

Table 1: Descriptive statistics

	Descriptive statistics					Direct effect of PO			
	Obs.	Mean	Std. Dev.	Min	Max	β| SG = 0	s.e.	β| SG = 1	s.e.
Coping mechanisms									
1. Self-generation (% of electricity) (SELFG)	21,482	25.47	29.38	0	100			3.03***	(0.50)
2. Fuel cost (% total costs) (FUEL)	39,791	3.87	5.89	0	40.11	0.02	(0.09)	0.25***	(0.10)
3. Active hours per week (HOURS)	59,201	64.32	34.71	0	168	1.34***	(0.33)	0.17	(0.54)
Outcome variables									
4. Capacity utilization (CAPACITY)	56,913	73.98	21.54	0	100	-0.78***	(0.30)	-0.46	(0.33)
5. Sales growth (SALEG)	43,496	8.38	14.17	-20	60	-0.20	(0.18)	-0.21	(0.16)
6. Labour productivity, log (Log_LP)	53,016	14.70	35.29	1.05	602	-0.01	(0.01)	0.01	(0.01)
Independent variables									
1. Power outage incidents region average (PO)	63,939	13.89	21.07	0	113.5				
2. Power outage duration region average (POD)	63,740	50.54	92.71	1.28	1201.27				

Table 2: Correlation results between different outcomes of firm performance

		1.	2.	3.	4.	5.	6.	7.	8.	9.
		SELFG	FUEL	HOURS	CAPACITY	SALEG	Log_LP	Log_PO	Log_POD	SG dummy
1.	SELFG	1								
2.	FUEL	0.18	1							
		(0.00)								
3.	HOURS	-0.06	-0.01	1						
		(0.00)	(0.22)							
4.	CAPACITY	-0.01	-0.03	0.13	1					
		(0.48)	(0.00)	(0.00)						
5.	SALEG	0.03	-0.01	0.01	0.05	1				
		(0.00)	(0.03)	(0.04)	(0.00)					
6.	Log_LP	-0.06	0.01	0.11	0.06	0.04	1			
		(0.00)	(0.01)	(0.00)	(0.00)	(0.00)				
7.	Log_PO	0.18	0.06	0.03	0.001	-0.04	0.09	1		
		(0.00)	(0.00)	(0.00)	(0.82)	(0.00)	(0.00)			
8.	Log_POD	0.35	0.09	0.02	-0.008	-0.02	0.08	0.83	1	
		(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)		
9.	SG dummy		0.07	0.13	0.06	-0.004	0.14	0.29	0.32	1
			(0.00)	(0.00)	(0.00)	(0.36)	(0.00)	(0.00)	(0.00)	

Note: The values in parenthesis indicate significance level of the correlation coefficients.

Table 3: The effect of power outages on firms with different power intensity: difference-in-differences estimates

	(1) SELFG	(2) FUEL	(3) HOURS	(4) CAPACITY	(5) SALEG	(6) Log_LP
Log_PO X PINT∣ SG = 0		0.017	-0.181**	-0.113*	-0.070**	-0.009***
		(0.019)	(0.085)	(0.061)	(0.033)	(0.003)
Log_PO X PINT∣ SG = 1	0.174**	-0.006	-0.158	-0.054	-0.070**	-0.008**
	(0.083)	(0.019)	(0.098)	(0.046)	(0.035)	(0.003)
Log_Age	-0.639*	-0.115	-0.418	-1.475***	-2.584***	0.009
	(0.381)	(0.083)	(0.442)	(0.268)	(0.190)	(0.012)
Medium size	0.323	-0.474***	4.492***	2.708***	0.575***	0.112***
	(0.507)	(0.088)	(0.432)	(0.324)	(0.202)	(0.015)
Large size	0.686	-0.904***	18.942***	7.195***	1.472***	0.176***
	(0.695)	(0.121)	(0.971)	(0.459)	(0.268)	(0.022)
Multi plant	0.010	-0.093	1.972***	0.598	0.288	0.098***
	(0.544)	(0.100)	(0.656)	(0.365)	(0.225)	(0.016)
Public	-2.913	1.535**	0.309	-6.650***	0.886	-0.035
	(1.823)	(0.693)	(1.880)	(1.283)	(0.785)	(0.055)
Foreign	-0.563	-0.074	3.575***	-0.236	0.142	0.141***
	(0.706)	(0.127)	(0.803)	(0.440)	(0.270)	(0.018)
Institutions	-0.232	0.207***	-0.691**	-1.794***	0.021	-0.000
	(0.438)	(0.056)	(0.340)	(0.293)	(0.130)	(0.009)
Credit Access	0.024***	0.001	0.023**	-0.024***	0.008**	0.002***
	(0.008)	(0.001)	(0.010)	(0.009)	(0.004)	(0.000)
SG dummy		0.741***	3.368***	0.877***	0.153	0.125***
		(0.111)	(0.593)	(0.334)	(0.200)	(0.017)
Constant	19.771***	3.497***	53.307***	90.715***	4.355***	1.094***
	(1.737)	(0.323)	(1.540)	(1.158)	(0.669)	(0.043)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.162	0.205	0.156	0.167	0.179

Notes: The regressions are based on Equation (1). The dependent variables are indicated in column headings and have been described in Table 1. Log_PO is the log of the average frequency of power outages across cities/regions. Power intensity (PINT) is measured at industry level using fuel consumption per person in billions of BTUs. The interaction term between Log_PO and PINT is further interacted with the self-generating dummy (SG dummy) so that it is separately estimated for non-self-generating firms (SG = 0) and self-generating firms (SG = 1). Country-city, industry and year effects dummies are included in all regressions. The standard errors given in parentheses are corrected for clustering by city-years.

Table 4: Difference-in-differences estimates including interaction terms for size and power intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	SELFG	FUEL	HOURS	CAPACITY	SALEG	Log_LP
Log_PO X PINT ∣ Small & SG = 0		0.014	-0.590***	-0.211**	-0.124**	-0.010**
		(0.028)	(0.116)	(0.091)	(0.048)	(0.004)
Log_PO X PINT ∣ Small & SG = 1	0.091	-0.069**	-0.375***	-0.065	-0.080	-0.012**
	(0.103)	(0.031)	(0.137)	(0.072)	(0.064)	(0.005)
Log_PO X PINT ∣ Medium & SG = 0		0.059***	-0.284*	-0.020	-0.050	-0.011***
		(0.023)	(0.148)	(0.076)	(0.046)	(0.004)
Log_PO X PINT ∣ Medium & SG = 1	0.175*	-0.022	-0.061	-0.085	-0.066	-0.010***
	(0.091)	(0.021)	(0.105)	(0.068)	(0.042)	(0.004)
Log_PO X PINT ∣ Large & SG = 0		-0.007	0.313	0.029	-0.070	-0.000
		(0.029)	(0.227)	(0.092)	(0.088)	(0.007)
Log_PO X PINT ∣ Large & SG = 1	0.231**	0.028	0.250	-0.026	-0.032	-0.004
	(0.097)	(0.027)	(0.153)	(0.068)	(0.044)	(0.007)
Log_PO∣ Small & SG = 0		-0.342***	3.603***	0.359	0.086	-0.007
		(0.115)	(0.817)	(0.310)	(0.191)	(0.024)
Log_PO∣ Small & SG = 1	-1.123**	0.072	1.930***	0.784***	0.073	0.027
	(0.529)	(0.097)	(0.742)	(0.292)	(0.175)	(0.020)
Log_PO∣ Medium & SG = 0		-0.187*	3.250***	-0.230	0.086	0.000
		(0.098)	(1.019)	(0.287)	(0.219)	(0.021)
Log_PO∣ Medium& SG = 1	-0.962*	-0.057	1.556**	0.220	-0.141	0.008
	(0.496)	(0.070)	(0.667)	(0.231)	(0.157)	(0.015)
Log_PO∣ Large& SG = 0		-0.025	2.296***	0.023	0.579**	0.007
		(0.102)	(0.746)	(0.316)	(0.252)	(0.020)
Log_Age	-0.599	-0.102	-0.522	-1.487***	-2.587***	0.009
	(0.379)	(0.084)	(0.433)	(0.268)	(0.191)	(0.011)
Medium size	-0.367	-0.597***	4.564***	3.430***	0.625**	0.119***
	(1.118)	(0.110)	(0.607)	(0.404)	(0.298)	(0.020)
Large size	-2.051	-1.141***	20.176***	7.923***	1.166***	0.176***
	(1.288)	(0.138)	(1.122)	(0.528)	(0.357)	(0.027)
Multi plant	-0.085	-0.115	2.073***	0.619*	0.275	0.098***
	(0.541)	(0.098)	(0.631)	(0.365)	(0.224)	(0.016)
Public	-3.047*	1.499**	0.288	-6.638***	0.846	-0.038
	(1.822)	(0.693)	(1.892)	(1.279)	(0.783)	(0.055)
Foreign	-0.366	-0.052	3.363***	-0.266	0.154	0.141***

	(0.709)	(0.126)	(0.773)	(0.438)	(0.268)	(0.018)
Institutions	-0.222	0.206***	-0.660*	-1.799***	0.022	-0.001
	(0.436)	(0.056)	(0.338)	(0.293)	(0.130)	(0.009)
Credit Access	0.024***	0.001	0.024**	-0.024***	0.008**	0.002***
	(0.008)	(0.001)	(0.010)	(0.009)	(0.004)	(0.000)
SG dummy		0.422***	6.166***	0.394	0.452*	0.103***
		(0.134)	(0.755)	(0.433)	(0.251)	(0.024)
Constant	22.558***	4.214***	46.813***	90.181***	4.043***	1.114***
	(2.118)	(0.347)	(2.447)	(1.222)	(0.742)	(0.061)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.163	0.207	0.157	0.167	0.180

Notes: The regressions are based on Equation (2). The dependent variables are indicated in column headings and have been described in Table 1. Log_PO is the log of the average frequency of power outages across cities/regions. Power intensity (PINT) is measured at industry level using fuel consumption per person in billions of BTUs. The interaction term between Log_PO and PINT is further interacted with the self-generating dummy (SG dummy) and firm size dummies (small, medium, and large) so that it is separately estimated for non-self-generating firms (SG = 0) and self-generating firms (SG = 1) across the three size groups. Country-city, industry and year effects dummies are included in all regressions. The standard errors given in parentheses are corrected for clustering by city-years.

Figures

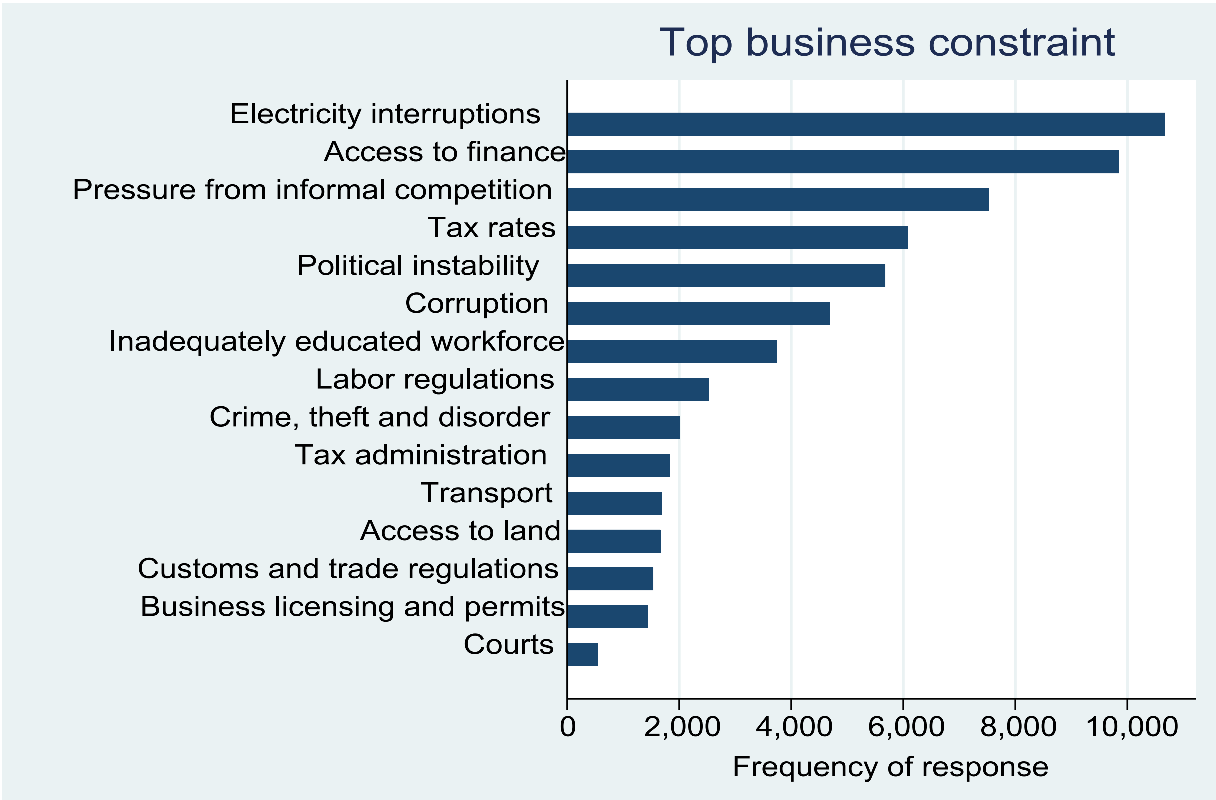

Figure 1: Frequency table of responses to most important constraint among manufacturing firms

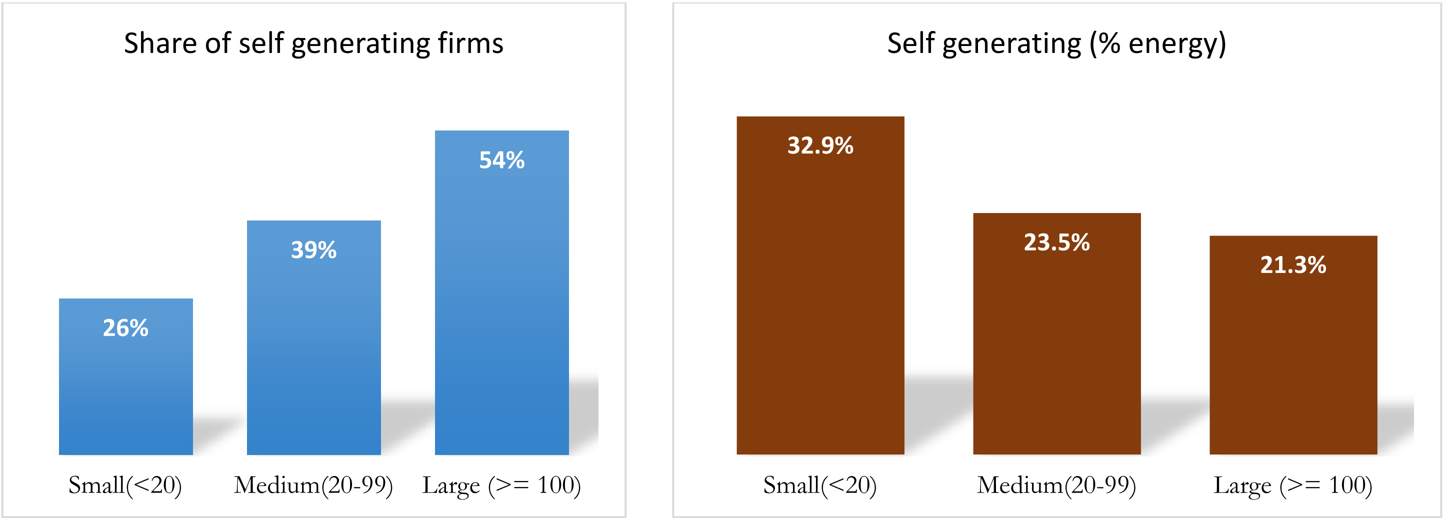

Figure 2: Self generating of electricity by size group

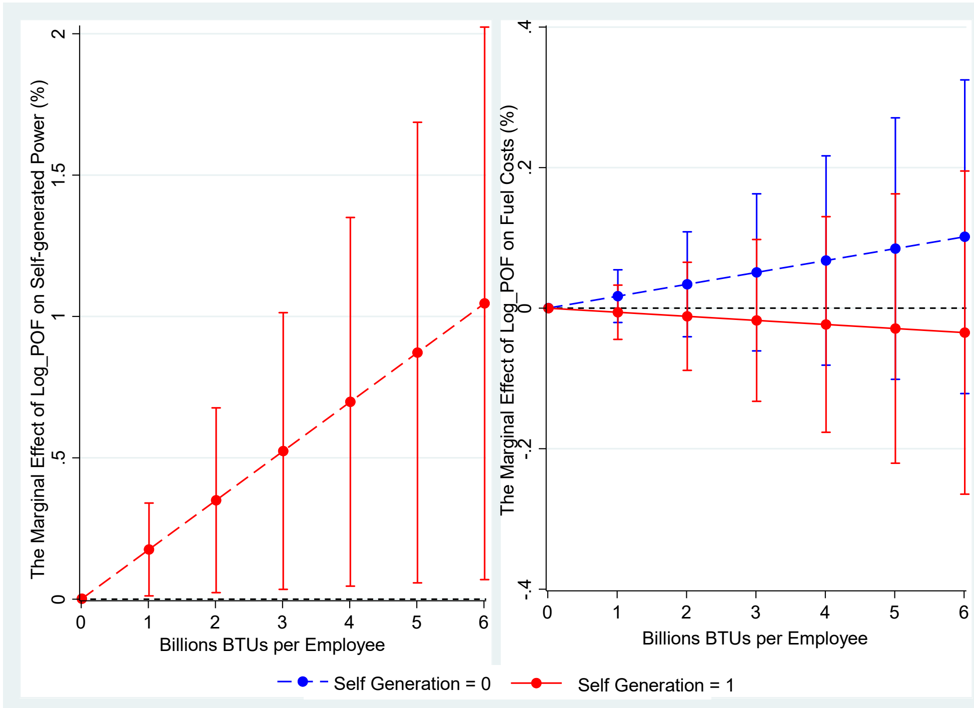

Figure 3: The marginal effect of power outages on in-house generation of electricity and fuel costs

Note: The blue and red vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms.

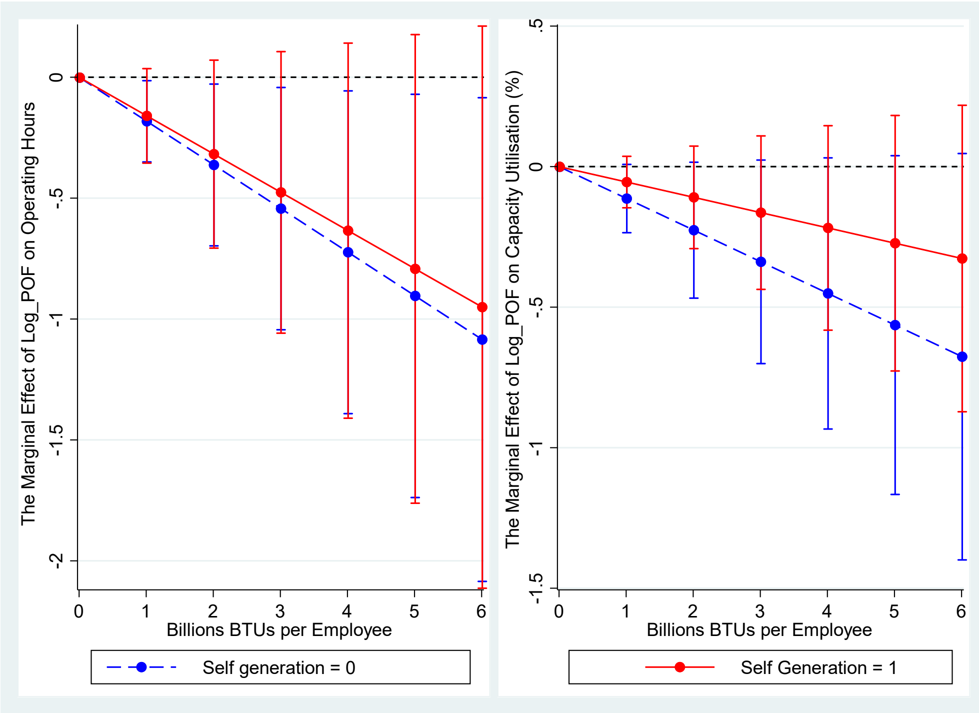

Figure 4: The marginal effect of power outages on active operating hours and capacity utilization

Note: The blue and red vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms.

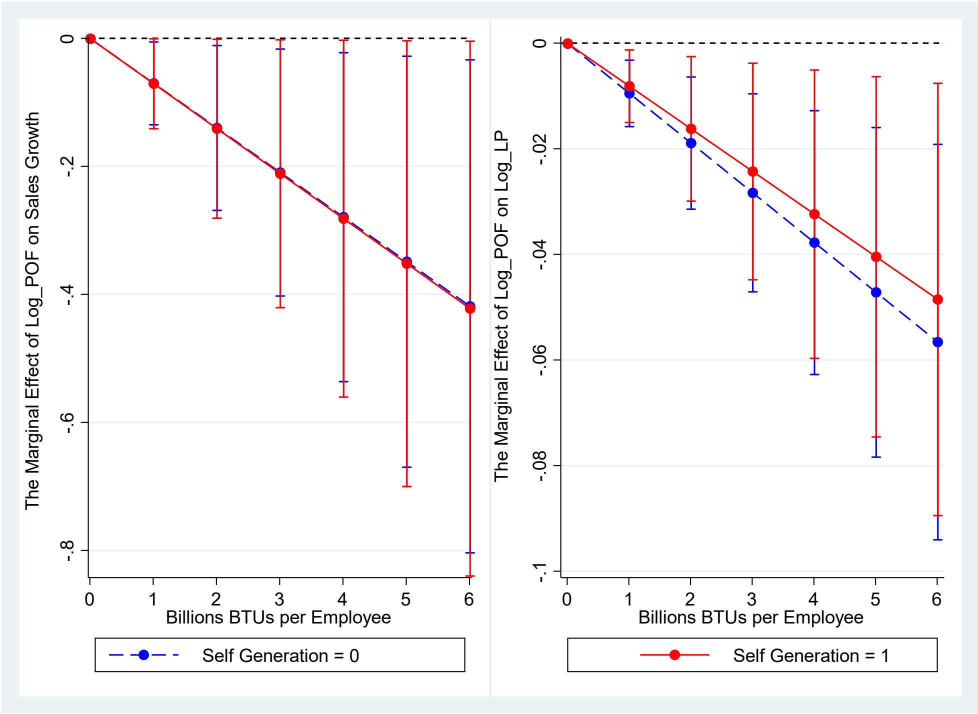

Figure 5: The marginal effect of power outages on sales growth and labour productivity

Note: The blue and red vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms.

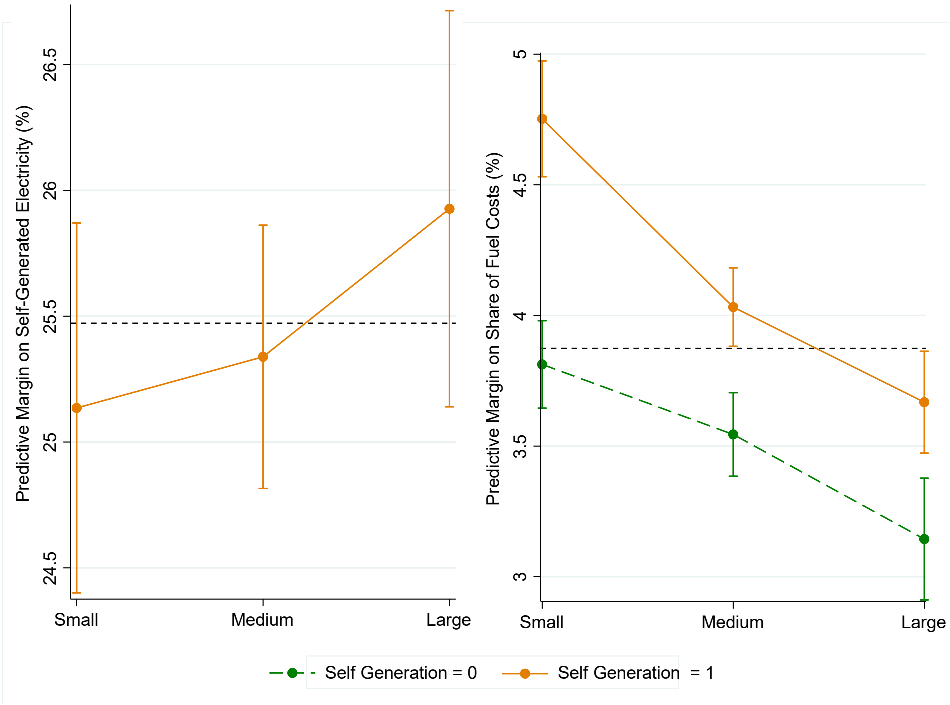

Figure 6: Predictive margins of in-house generation of electricity and fuel costs

Note: The green and orange vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms. The dashed black lines indicate the overall mean of the predicted outcome variable.

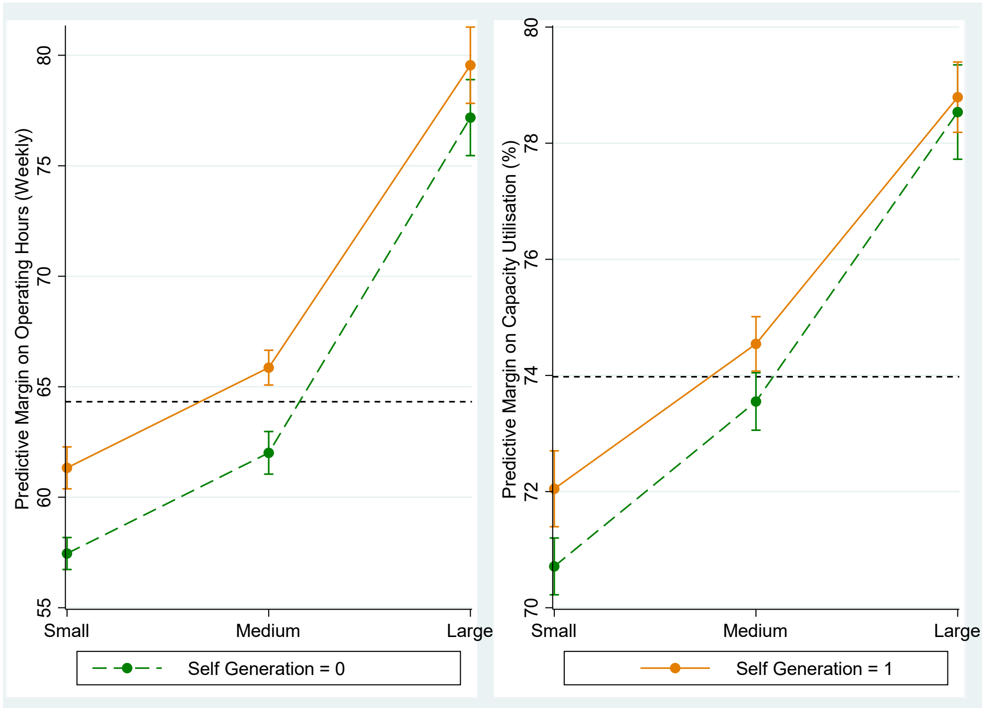

Figure 7: Predictive margins of active operating hours and capacity utilization

Note: The green and orange vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms. The dashed black lines indicate the overall mean of the predicted outcome variable.

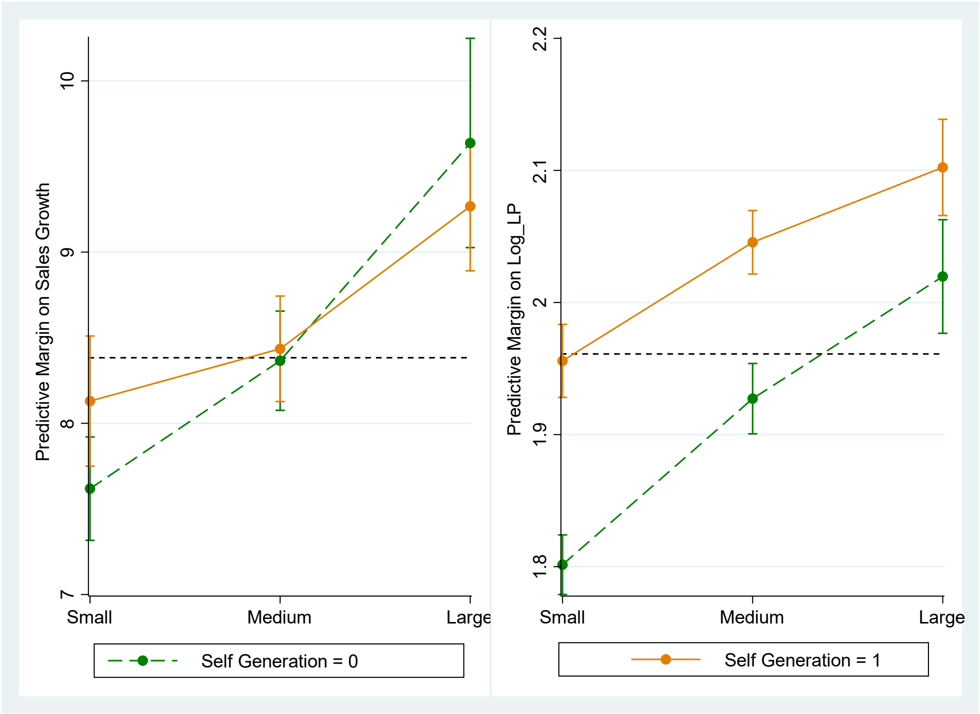

Figure 8: Predictive margins of sales growth and labour productivity for size groups

Note: The green and orange vertical lines with spikes represent the 95% confidence bands, respectively, for non-generating and generating firms. The dashed black lines indicate the overall mean of the predicted outcome variable.

APPENDICES

Table A1: Descriptive statistics of other variables for subsamples of self-generating and non-self-generating firms

	Full sample					Non-generating firms					Generating firms				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Dependent variables															
1. Fuel cost (% total costs)	39,643	3.87	5.88	0	40.11	24,956	3.55	5.59	0	40	14,687	4.43	6.31	0	40.11
2. Self-generation (% of electricity)	21,481	25.47	29.37	0	100	0	.	.	.	.	21,481	25.47	29.37	0	100
3. Active hours per week	58,967	64.34	34.71	0	168	37,044	60.96	31.97	0	168	21,923	70.05	38.23	0	168
4. Capacity utilization	56,714	73.98	21.53	0	100	35,718	72.94	21.92	0	100	20,996	75.75	20.74	0	100
5. Sales growth	42,494	8.33	14.13	-20	60	26,246	8.38	14.50	-20	60	16,248	8.25	13.51	-19.93	60
6. Labour productivity (LP)	51,666	14.59	34.78	1.05	602.37	32,102	12.84	32.83	1.05	602.37	19,564	17.47	37.59	1.05	600
Independent variables															
1. PO frequency region average (PO)	62,321	13.97	21.04	0	113.48	38,953	10.02	17.82	0	113.48	23,368	20.57	24.10	0	113.48
2. PO duration region average (POD)	62,142	3.71	2.81	0.67	36.73	38,781	3.47	2.32	0.67	36.73	23,361	4.10	3.45	0.69	36.73
Control variables															
1. Small size	62,321	0.40	0.49	0	1	38,953	0.47	0.50	0	1	23,368	0.28	0.45	0	1
2. Medium size	62,321	0.36	0.48	0	1	38,953	0.35	0.48	0	1	23,368	0.37	0.48	0	1
3. Large size	62,321	0.24	0.43	0	1	38,953	0.17	0.38	0	1	23,368	0.34	0.48	0	1
4. Age	61,551	28.42	17.17	2	349	38,471	28.01	16.47	2	322	23,080	29.09	18.26	2	349
5. Multi-plant firms	60,120	0.16	0.37	0	1	37,612	0.12	0.33	0	1	22,508	0.23	0.42	0	1
6. Publicly owned firms	61,431	0.01	0.11	0	1	38,346	0.01	0.11	0	1	23,085	0.02	0.13	0	1
7. Foreign owned firms	61,400	0.10	0.31	0	1	38,328	0.09	0.28	0	1	23,072	0.14	0.34	0	1
8. Credit access (%)*	57,640	14.81	25.78	0	100	35,652	12.78	24.24	0	100	21,988	18.10	27.78	0	100
9. Institutional quality	62,276	1.43	0.87	0	4	38,922	1.40	0.89	0	4	23,354	1.47	0.84	0	4
Instrumental variables**															
1. Limited water shortage (<1 interruptions /month)	54,982	0.89	0.31	0	1	34,325	0.91	0.28	0	1	20,657	0.86	0.35	0	1
2. Moderate water shortage (1-5 interruptions /month)	54,982	0.06	0.23	0	1	34,325	0.05	0.22	0	1	20,657	0.07	0.25	0	1
3. High water shortage (6-10 interruptions /month)	54,982	0.02	0.13	0	1	34,325	0.01	0.11	0	1	20,657	0.03	0.16	0	1
4. Severe water shortage (>10 interruptions /month)	54,982	0.03	0.18	0	1	34,325	0.02	0.15	0	1	20,657	0.05	0.21	0	1

Notes: *Credit access is measured using the percentage share of credit in total working capital. ** The instrumental variables are dummy variables that indicate the degree of water shortage, measured as number of interruption incidents per month.

Table A2: Measures of energy intensity

	(1) PINT	(2) PINT2	(3) PINT3
	Energy consumption in BTUs per employee (billions)	Energy cost (% of Sales)	Energy consumption in BTUs per USD of sales shipment (000s)
15 - Food products and beverages	0.798	1.743	1.296
16 - Tobacco products	0.735	0.295	0.200
17 - Textiles	0.390	2.259	1.457
18 - Wearing apparel; dressing and dyeing of fur	0.072	0.771	0.600
19 - Tanning and dressing of leather	0.116	0.669	0.400
20 - Wood and products of wood and cork	1.162	2.459	4.300
21 - Paper and paper products	6.389	4.349	11.400
22 - Publishing, printing & recorded media	0.235	1.514	1.000
24 - Chemicals and chemical products	4.959	3.352	4.400
25 - Rubber and plastics products	0.375	1.927	1.300
26 - Other non-metallic mineral products	2.174	4.588	7.300
27 - Basic metals	4.430	4.483	6.300
28 - Fabricated metal products	0.232	1.565	0.900
29 - Machinery and equipment n.e.c.	0.156	0.843	0.400
30 - Office, accounting and computing machinery	0.183	0.446	0.500
31 - Electrical machinery and apparatus n.e.c.	0.245	0.882	0.600
32 - Radio, television and communication	0.2	0.7	0.6
33 - Medical, precision and optical instruments	0.2	0.6	0.6
34 - Motor vehicles, trailers and semi-trailers	0.5	0.6	0.3
35 - Other transport equipment	0.2	0.7	0.4
36 - Furniture; manufacturing n.e.c.	0.1	1.5	0.5
37 - Recycling	0.1	-	0.3

Notes: Energy consumption per employee in billions of British Thermal Units (BTUs) and energy consumption per USD of sales shipment in thousands of BTUs is based on US data from the *Manufacturing Energy Consumption Survey* dataset undertaken by the US Energy Information Administration Agency (EIA). The data is based on the most recent available year of the survey, which is 2014. Energy cost as a percentage of total sectoral sales shipment were computed using data from the NBER-CES Manufacturing Industry Database.

Table A3: Difference-in-differences results using an alternative measure of power intensity

	(1) SELFG	(2) FUEL	(3) HOURS	(4) CAPACITY	(5) SALEG	(6) Log_LP
Equation 1						
Log_PO X PINT2 ǀ SG = 0		-0.022	-0.315**	-0.108	-0.068	-0.013**
		(0.040)	(0.145)	(0.082)	(0.046)	(0.005)
Log_PO X PINT2 ǀ SG = 1	0.342**	-0.022	-0.524***	-0.083	-0.091*	-0.010*
	(0.147)	(0.033)	(0.136)	(0.079)	(0.050)	(0.006)
Observations	19,126	35,296	51,210	49,590	37,750	45,462
R-squared	0.453	0.161	0.205	0.156	0.167	0.179
Equation 2						
Log_PO X PINT2 ǀ Small & SG = 0		-0.045	-1.137***	-0.143	-0.119*	-0.015**
		(0.061)	(0.156)	(0.107)	(0.069)	(0.006)
Log_PO X PINT2 ǀ Small & SG = 1	0.308*	-0.159***	-0.866***	-0.078	-0.085	-0.013*
	(0.181)	(0.048)	(0.163)	(0.103)	(0.089)	(0.007)
Log_PO X PINT2 ǀ Medium & SG = 0		0.093*	-0.533***	0.007	-0.100	-0.015**
		(0.048)	(0.168)	(0.130)	(0.063)	(0.007)
Log_PO X PINT2 ǀ Medium & SG = 1	0.319**	-0.023	-0.341**	-0.216*	-0.077	-0.016***
	(0.155)	(0.036)	(0.163)	(0.129)	(0.061)	(0.006)
Log_PO X PINT2 ǀ Large & SG = 0		0.035	0.595	0.074	-0.025	0.004
		(0.051)	(0.365)	(0.124)	(0.120)	(0.010)
Log_PO X PINT2 ǀ Large & SG = 1	0.467***	0.035	0.432*	-0.040	-0.044	-0.001
	(0.162)	(0.047)	(0.252)	(0.102)	(0.064)	(0.011)
Observations	19,126	35,296	51,210	49,590	37,750	45,462
R-squared	0.453	0.164	0.208	0.156	0.167	0.180

Notes: Country-city, year, and industry dummies and a set of control variables are included but not reported. Alternative power intensity (PINT2) is measured at industry level using fuel consumption per dollar of sales shipment in thousands of BTUs.

Table A4: Difference-in-differences results using an alternative measure of power intensity

	(1) SELFG	(2) FUEL	(3) HOURS	(4) CAPACITY	(5) SALEG	(6) Log_LP
Equation 1						
Log_PO X PINT3 | SG = 0		-0.002	-0.185***	-0.057	-0.026	-0.007***
		(0.022)	(0.060)	(0.041)	(0.023)	(0.002)
Log_PO X PINT3 | SG = 1	0.147**	-0.013	-0.247***	-0.045	-0.040	-0.005**
	(0.074)	(0.017)	(0.071)	(0.037)	(0.025)	(0.002)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.162	0.205	0.156	0.167	0.179
Equation 2						
Log_PO X PINT3 | Small & SG = 0		-0.025	-0.466***	-0.076	-0.038	-0.008***
		(0.030)	(0.075)	(0.051)	(0.032)	(0.003)
Log_PO X PINT3 | Small & SG = 1	0.131	-0.067***	-0.368***	-0.028	-0.040	-0.005*
	(0.089)	(0.024)	(0.081)	(0.046)	(0.042)	(0.003)
Log_PO X PINT3 | Medium & SG = 0		0.045*	-0.230***	-0.017	-0.041	-0.008**
		(0.024)	(0.089)	(0.057)	(0.032)	(0.003)
Log_PO X PINT3 | Medium & SG = 1	0.149*	-0.016	-0.182**	-0.093	-0.041	-0.008***
	(0.078)	(0.019)	(0.078)	(0.057)	(0.029)	(0.003)
Log_PO X PINT3 | Large & SG = 0		0.022	0.175	0.019	-0.011	-0.001
		(0.027)	(0.186)	(0.063)	(0.059)	(0.005)
Log_PO X PINT3 | Large & SG = 1	0.177**	0.033	0.107	-0.026	-0.013	-0.001
	(0.078)	(0.027)	(0.124)	(0.048)	(0.034)	(0.004)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.164	0.207	0.156	0.167	0.180

Notes: Country-city, year, and industry dummies and a set of control variables are included but not reported. Alternative power intensity (PINT3) is measured at industry level based on energy consumption in BTUs per USD of sales shipment (000s).

Table A5: Results using duration-based measure of power outage

	(1) SELFG	(2) FUEL	(3) HOURS	(4) CAPACITY	(5) SALEG	(6) Log_LP
Equation 1						
Log_PO X PINT∣ SG = 0		0.009	-0.254***	-0.134**	-0.049	-0.009***
		(0.017)	(0.086)	(0.057)	(0.036)	(0.003)
Log_PO X PINT∣ SG = 1	0.190**	-0.011	-0.176**	-0.073	-0.058	-0.006**
	(0.081)	(0.015)	(0.080)	(0.045)	(0.036)	(0.003)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.162	0.205	0.156	0.167	0.179
Equation 2						
Log_PO X PINT∣ Small & SG = 0		-0.003	-0.506***	-0.191***	-0.089**	-0.010***
		(0.022)	(0.096)	(0.073)	(0.043)	(0.004)
Log_PO X PINT ∣ Small & SG = 1	0.126	-0.052**	-0.334***	-0.066	-0.073	-0.009***
	(0.087)	(0.023)	(0.098)	(0.060)	(0.053)	(0.003)
Log_PO X PINT ∣ Medium & SG = 0		0.044**	-0.265**	-0.074	-0.026	-0.009**
		(0.019)	(0.113)	(0.067)	(0.041)	(0.004)
Log_PO X PINT ∣ Medium & SG = 1	0.212**	-0.017	-0.090	-0.081	-0.060	-0.007**
	(0.085)	(0.018)	(0.092)	(0.059)	(0.039)	(0.003)
Log_PO X PINT ∣ Large & SG = 0		0.012	0.320*	0.023	-0.035	-0.001
		(0.024)	(0.182)	(0.079)	(0.074)	(0.005)
Log_PO X PINT ∣ Large & SG = 1	0.235**	0.017	0.147	-0.031	-0.018	-0.002
	(0.093)	(0.020)	(0.111)	(0.060)	(0.043)	(0.005)
Observations	19,166	35,352	51,307	49,680	37,819	45,552
R-squared	0.452	0.164	0.207	0.157	0.167	0.180

Table A6: First stage results for predicting power outage using water shortages

	(1) Log_PO	(2) Log_PO
Moderate water shortage dummy	-0.005	
	(0.016)	
High water shortage dummy	0.138***	
	(0.027)	
Severe water shortage dummy	0.206***	
	(0.022)	
Minimal water shortage dummy ∣ SG = 0		-0.346***
		(0.035)
Minimal water shortage dummy ∣ SG = 1		-0.280***
		(0.034)
Moderate water shortage dummy ∣ SG = 0		-0.306***
		(0.039)
Moderate water shortage dummy ∣ SG = 1		-0.335***
		(0.042)
High water shortage dummy ∣ SG = 0		-0.174***
		(0.061)
High water shortage dummy ∣ SG = 1		-0.168***
		(0.047)
Severe water shortage dummy ∣ SG = 0		-0.231***
		(0.044)
Severe water shortage dummy ∣ SG = 1		0.000
		(0.000)
Log(Age)	-0.009	-0.009
	(0.009)	(0.013)
Medium size dummy	-0.011	-0.011
	(0.010)	(0.015)
Large size dummy	-0.047***	-0.047***
	(0.013)	(0.018)
Multi-plant dummy	-0.004	-0.002
	(0.012)	(0.016)
Public owned	-0.083**	-0.082
	(0.040)	(0.056)
Foreign owned	0.006	0.006

	(0.014)	(0.017)
Institutional quality	0.049***	0.049***
	(0.006)	(0.011)
Credit access	0.000	0.000
	(0.000)	(0.000)
Self-generation dummy	0.063***	
	(0.010)	
Constant	1.816***	2.160***
	(0.184)	(0.055)
Observations	29,444	29,444
R-squared	0.738	0.738

Notes: Power outage is measured at firm level using self-reported values for the number of power interruptions in a typical month. The water shortage dummies are operationalized as follows: *Minimal* water shortage dummy captures < 1 water interruptions /month. *Moderate* water shortage dummy captures 1-5 water interruptions /month. *High water* shortage dummy captures 6-10 water interruptions /month. Severe water shortage dummy indicates >10 interruptions /month. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A7: Results using instrumented measures of power outage

	(1) SELFG	(2) FUEL	(3) HOURS	(4) CAPACITY	(5) SALEG	(6) Log_LP
Equation 1						
Log_PO X PINT∣ SG = 0		0.037	-0.287**	-0.115	-0.100**	-0.017***
		(0.026)	(0.123)	(0.087)	(0.045)	(0.004)
Log_PO X PINT∣ SG = 1	0.240**	-0.000	-0.204*	-0.064	-0.102**	-0.012***
	(0.097)	(0.023)	(0.121)	(0.058)	(0.047)	(0.004)
Observations	19,171	35,474	51,466	49,838	37,964	45,704
R-squared	0.452	0.167	0.205	0.157	0.167	0.179
Equation 2						
Log_PO X PINT ∣ Small & SG = 0		0.020	-0.714***	-0.210*	-0.145***	-0.016***
		(0.034)	(0.149)	(0.108)	(0.055)	(0.005)
Log_PO X PINT ∣ Small & SG = 1	0.144	-0.058*	-0.439***	-0.064	-0.105	-0.015***
	(0.118)	(0.035)	(0.161)	(0.082)	(0.074)	(0.005)
Log_PO X PINT ∣ Medium & SG = 0		0.084***	-0.413**	-0.020	-0.088	-0.019***
		(0.027)	(0.191)	(0.096)	(0.057)	(0.005)
Log_PO X PINT ∣ Medium & SG = 1	0.250**	-0.011	-0.103	-0.083	-0.103**	-0.014***
	(0.105)	(0.024)	(0.132)	(0.080)	(0.051)	(0.004)
Log_PO X PINT ∣ Large & SG = 0		0.026	0.457	0.109	-0.123	-0.008
		(0.034)	(0.279)	(0.125)	(0.115)	(0.008)
Log_PO X PINT ∣ Large & SG = 1	0.289***	0.041	0.240	0.004	-0.064	-0.006
	(0.106)	(0.029)	(0.177)	(0.078)	(0.053)	(0.008)
Observations	19,171	35,474	51,466	49,838	37,964	45,704
R-squared	0.452	0.168	0.208	0.157	0.167	0.180

Mission

To strengthen local capacity for conducting independent,
rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

Bringing Rigour and Evidence to Economic Policy Making in Africa

- Improve quality.
- Ensure Sustainability.
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