A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

Essays on Business Environment and Firm Performance

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Acknowledgments

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Abstract

Firm performance is central to economic growth of developing economies. However, it is affected by the business environments in which a firm operates. These business environments includes: features of legal and regulatory services, infrastructures, financial and institutional systems of the country. A burgeoning literature within development economics seeks to understand the constraints that a firm face and strategies to cope with these problems. However, a rigorous empirical study that informs policy makers and concerned development institutions is still lacking especially in Sub-Sahara African countries where the problem is severe.

Thus, this thesis focused on examining the impact of business environment on firm performance and how firms respond to poor business environment. The study mainly focused on examining the impact of poor electricity supply, its economic cost and how firms responds to a poor power supply.

The thesis is organized in two chapters. The first chapter "*power outages, economic cost and firm performance: Evidence from Ethiopia*"deals with how firms in Ethiopia respond to power interruptions and estimating the economic cost of power outages using two rounds of firm-level survey data. The study employed the World Bank Enterprise Survey (WBES) data collected from firms operating in Ethiopia during 2011 and 2015. The result shows that firms in Ethiopia self-generate electricity in response to power outages. Power outages were found to affect firms' productivity negatively, increasing firms' costs by 15% from 2011 to 2015. This effect varied negatively with output level, suggesting that power outages is particularly costly for small firms. This chapter is a single authored paper and published in the *Journal of Utilities Policy (53) 111-120*[1].

The second chapter "*firm performance under infrastructure constraint: evidence from Sub-Saharan African firms*" deals with the role of investment in self-generation in mitigating outage loss and evaluating the outage loss differential between firms

[1]The article can be accessed from: https://doi.org/10.1016/j.jup.2018.06.009

that invested in self-generation and those that didn't. Using the WBES data collected from firms operating in 13 Sub-Saharan African countries, the study provided an evidence that though self-generation has helped firms reduce outage loss, firms that have invested in self-generation continue to face higher unmitigated outage loss compared to firms without such investment. In spite of this, firms that have invested in self-generation would have incurred 36%-99% more than their current outage loss if they didn't engage in self-generation while firms that didn't invest in self-generation would have reduced their outage loss by 2% - 24% if they had engaged in self generation. This chapter is also a single authored paper.

Given the above result, the study proposed a differential supply interruption to be followed by public authorities based on firms' degree of vulnerability. Stating differently, firms whose operation are more vulnerable to power outages should get preferential power supply advantage. This could be possible by arranging a binding contract between a vulnerable firms and power companies, so that power companies charge an optimal tariff for supplying secure power for vulnerable firms. In turn, firms should be compensated if the power companies fail to do so. This helps vulnerable firms expand their production without fearing the risk of power outage.

Keywords: Power Outages, Firm, Self-generation Sub-Sahara Africa, Ethiopia

1 Power Outages, Economic Cost and Firm Performance: Evidence from Ethiopia

Abstract

The lack of secure and reliable electrical power is a constraint to doing business in developing countries. Industrial firms in developing countries adopt different strategies to cope with deficiencies in electricity supply. This paper employs the World Bank Enterprise Survey data to examine how firms in Ethiopia respond to power outages and estimate the resulting economic cost of power outages. The results show that firms in Ethiopia self-generate electricity in response to power outages. Power outages were found to affect firms' productivity negatively, increasing firms' costs by 15% from 2011 to 2015. This effect varied negatively with output level, suggesting that outage is particularly costly for small firms.

Keywords: Power outages, Self-generation, Firm, Ethiopia

1.1 Introduction

Ethiopia has electricity generating potential of 650 TWh per year, of which 40% is technically feasible. This constitutes 15% of total technically feasible potential of Africa (Federal Democratic Republic of Ethiopia, 2012). Currently, the country has about 2,421MW of installed power generating capacity, of which 87% comes from hydropower (Ethiopian Electric Power, 2015).

Even though the country has substantial electricity generating potential and there have been marginal improvements in recent years, the country is still characterized by being one of the least electrified in the World and has low per capita electricity consumption. Frequent and prolonged power outages and this poor supply of electricity are a major constraint to doing business faced by the industrial sectors. The country is also poorly ranked on the Ease of Doing Business index, published annually by the World Bank, ranking 161th out of 190 countries considered(World Bank, 2017).

The 2011 World Bank Enterprise Survey (WBES) report shows that electricity is the most severe constraint to doing business accounting for approximately 25% for average large industries and approximately12% for average medium industries. In 2015, electricity was the second largest constraint to doing business in Ethiopia, accounting for 10%, next to lack of access to finance (World Bank, 2015).

Poor supply of electricity can increase industrial firm's costs, steering their technological choices away from energy-intensive technology and increasing the overall cost of production. This further affects firm's competitiveness by causing firms to resort to alternative methods, which reduces product quality, halts production, and delays order delivery. A poor supply of electricity also affects investment decisions and firm location. This has a negative cumulative effect on a firm's growth. Abeberese (2016) shows that, in countries where the supply of electricity is highly unreliable, "firms lack the incentive to either move to productivity-enhancing industries or grow larger, since doing so comes with the cost of relying on electricity."

Given the prevalence of power outages, firms may respond in several ways to mitigate the associated outage costs. The commonly-adopted coping strategy is investment in self-generation. However, investment in self-generation undermines firms' productivity by forcing firms to channel their finances to less productive investment. Existing empirical evidence shows that self-generation of electricity is costlier than the electricity from the public grid (Steinbuks and Foster, 2010; Oseni and Pollitt, 2015; Adenikinju, 2003). The high cost of self-generation contributes to a fall in productivity through its impact on capital utilization in the short-term by inducing firms to reallocate and selectively utilize the most electricity-efficient way of production and substitute electricity for material inputs (Fisher-Vanden et al., 2015). This indicates that a higher cost of electricity may induce firms to alter input utilization, which forces them to operate below their full capacity. This could also further induce firms to invest in electricity efficient technology in the long term.

The way that firms respond to power outages partly depends on the nature of power outages. A firm may choose either to invest in backup energy or to outsource production of electricity-intensive intermediate inputs. However, it is not clear from the few previous studies whether power outages either lead to electricity efficiency or force firms to substitute electricity by material input. In this regard, Fisher-Vanden et al. (2015) provided a comprehensive empirical study, using a translog cost function, how Chinese industrial firms respond to electricity shortages. While the study shows how Chinese firms respond to electricity shortages, it is difficult to infer the equivalent result for firms in Ethiopia due to differences in the nature and severity of power supply interruptions in the two countries. This study, like that of Fisher-Vanden et al. (2015), employs a translog cost function in estimating the economic cost of power outages. However, this study used actual firm level outage data reported by firm themselves unlike that of (Fisher-Vanden et al., 2015). The authors used industry-level estimates of the ratio of thermal electricity generated to thermal electricity capacity as a measure of power shortages. Furthermore, this paper focuses on firms in SSA where the problem of power outage is more severe.

The purpose of this study is, therefore, to investigate how firms in Ethiopia respond to power interruptions and estimate the resulting economic cost using two rounds of firm-level survey.

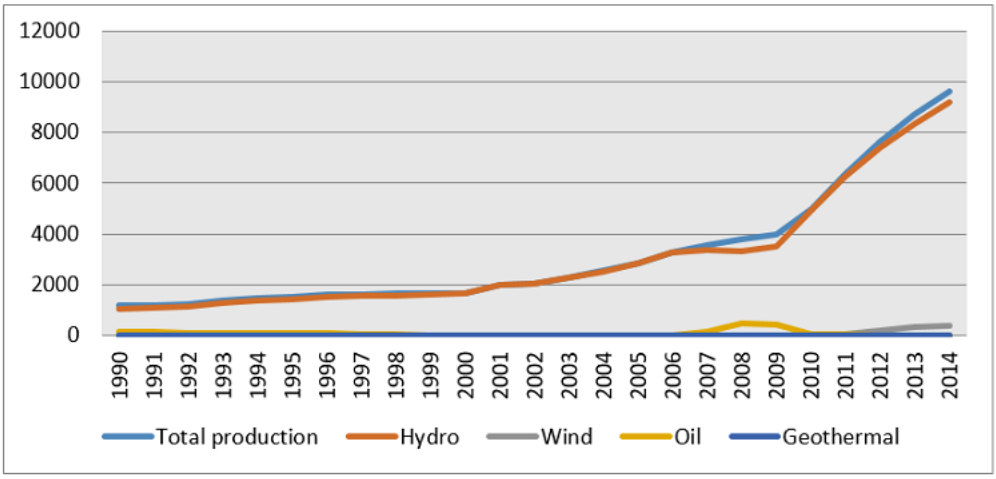
The remaining part of the study is organized as follows: section 2.2 presents an overview of electricity production and consumption in Ethiopia. Conceptual framework and hypothesis of the study are discussed in Section 1.3 while review of related literature is presented in section 2.4. Data sources and descriptions, estimation strategies, and the empirical model are discussed in section 1.5. Section 1.6 presents the empirical results. Conclusions drawn from the study and resulting policy implications are presented in section 1.7.

1.2 Overview of Electricity Production and Consumption in Ethiopia

Ethiopia has electricity generation potential of more than 45,000 MW from hydropower; of which 30,000 MW is economically feasible which is equivalent to an electricity generation of 162 TWh. The country has untapped potential in the areas of geothermal and wind which has an electricity generating potential of 5,000 MW and 10,000 MW respectively. However, only a fraction of this potential has been harnessed so far. Currently, Ethiopia has around 2,421MW of installed power generating capacity, out of which 87% (Figure 1.1) is generated from hydropower (Ethiopian Electric Power, 2015).

Even though there is a huge improvement in electricity generation of the country, the electricity supply in the country is far below satisfying the growing demand. Demand for electricity is growing by more than 25% (Ethiopian Electric Power Corporation, 2012). This is attributed to high population and economic growth, expansion of grid extension to rural towns and villages, and shifts in household energy consumption in major towns from wood-fuel and kerosene to electricity.

Figure 1.1: Electricity Production by Source (GWh)

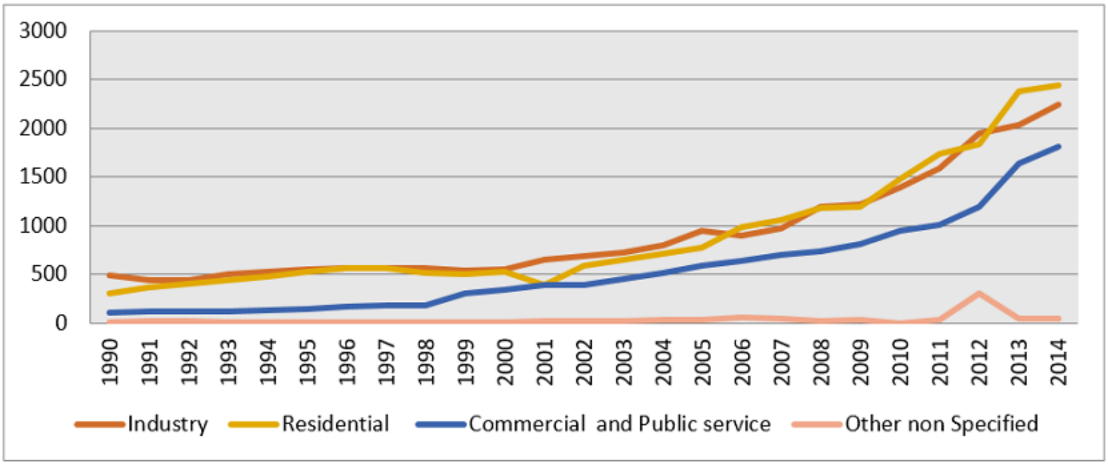


Source: IEA,2014

Power consumption in the country has increased significantly following economic growth the country has been experiencing since 2005. The country's economy has been growing at a staggering averaging Gross Domestic Product (GDP) growth rate of 10.8% since 2005 with all the major sectors of the economy have shown a remarkable leap forward (MoFED, 2010). In line with this economic growth, power consumption in the country has increased significantly. The total final electricity consumption has increased from 907 GWh in 1990 to more than 6529 GWh in 2014 (International Energy Agency, 2014).

In terms of sector, industrial sector was the end-use sector that on average consumed the most delivered electricity till end of 2005/06 followed by households (Figure 1.2). The rural electrification program of the government and a shift from wood-fuel and kerosene to electricity for cooking in major cities of the country has triggered household consumption of electricity to increase significantly after 2010/11(Federal Democratic Republic of Ethiopia, 2012).

Figure 1.2: Electricity Consumption by Sector (1990-2014) in GWh



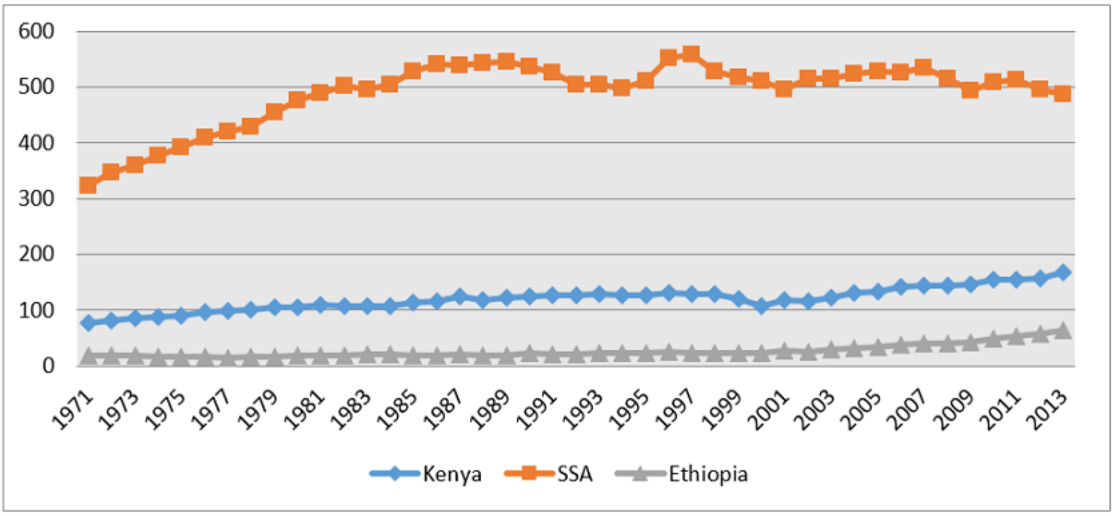
Source: IEA, 2014

However, Ethiopia is still among countries characterized by least electrified and low electricity consumption per capita. Much of the country's energy demand comes from biofuels and wastes. While world electricity consumption has been steadily increasing over the past decades, Ethiopia's electric power consumption per capita doesn't show much improvement International Energy Agency (2014). The country's annual electricity per capita consumption has shown sluggish improvement from 18 KW per capita in 1971 to 65 KW per capita in 2013. As it was shown below (Figure 1.3), this is much below even the average Sub-Saharan Africa (SSA) which is 324 KW per year in 1971 and 488 KW per year in 2013 (World Bank, 2016).

Even though a lack of access to electricity is a problem for many of the SSA countries, Ethiopia is poorly ranked in terms of energy progress. According to International Energy Agency (2014), about 69 million people in Ethiopia lack access to electricity. The country is poorly rated on energy indicators. Bersisa (2016) found the energy poverty rate in Ethiopia is 74 per cent and 73 per cent in 2011 and 2014 respectively. Ethiopia was least ranked based on IEA's Energy Development Index (EDI) in

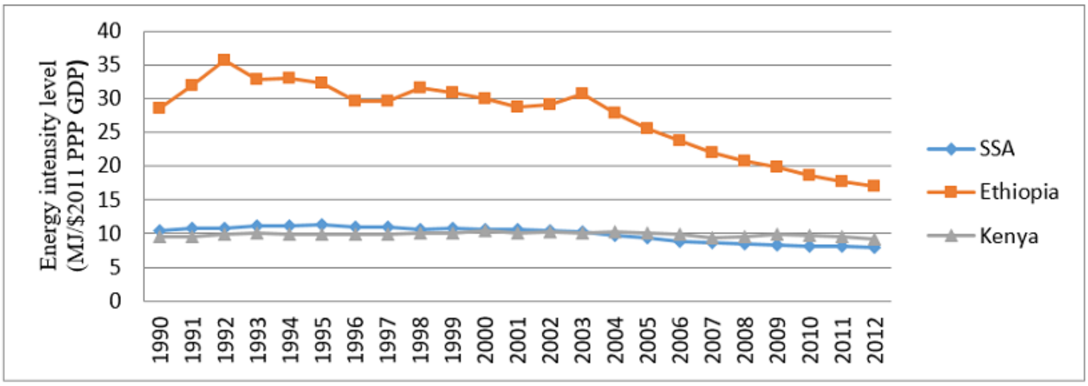
2012 with EDI score of 0.04. Similarly, on Oxford University's Multidimensional Energy Poverty Index (MEPI), which measure the incidence and intensity of energy poverty, Ethiopia has a score of 0.9 with one showing total deprivation or suffer from acute energy poverty. The energy intensity level of Ethiopia has declined from 28.63 MJ/GDP in 1990 to 17 MJ/GDP in 2012. Even though there is an improvement in recent years, the figure is even much higher than the SSA which is 10.44 MJ/GDP and 7.9 GDP respectively for the year under consideration. This implies that Ethiopia requires more energy to produce a unit of output or undertake a given activity than other average SSA countries need.

Figure 1.3: Electricity Power Consumption Per Capita (KWh per capita)



Source: World Bank, 2016

Figure 1.4: Electricity Intensity Level (MJ/GDP)



Source: WB/WDI, 2016

1.3 Conceptual Framework

Assume a production function with five inputs: capital (K), labor (L), material (M), electricity (E) and non-electric energy (N). Following the approach of Fisher-Vanden et al. (2015), a firm's response to power outages can be inferred from the changes in input utilization due to a lack of electricity. Assume that a firm using these inputs produces output Q,

$$Q = F(K,\ L,\ M,\ E,\ N,\ S) \tag{1.1}$$

where S denotes the probability of blackouts, which measures resource inadequacy. If the supply of electricity is reliable, i.e. $S = 0$, the dual of the unconstrained cost function of the above production functions is given as:

$$C_u = C_u(P_k,\ P_l, P_m,\ P_e,\ P_n,\ Q) \tag{1.2}$$

Using the Shephard's Lemma, the optimal demand for factor input is given as:

$$X_i \quad = \quad \frac{\partial C_u(P_k,\ P_{l,}\ P_m,\ P_e,\ P_n,\ Q)}{\partial P_x} \tag{1.3}$$

where $X_i = K, L, M, E, N$

Assuming the production function takes the form of log-linear, an expression for value share of factor inputs can be derived as:

$$\frac{\partial lnC_u}{\partial P_x} \quad = \quad \frac{\partial C}{\partial Px}\frac{P_x}{C} = \frac{X_i^* P_x}{C} \tag{1.4}$$

where $X_i = K, L, M, E, N$

It can be supposed that there is some probability that the electricity supply is unreliable. The measure of electricity unreliability is normalized into one so that it shows the probability that a firm faces one day of power cut in a year, i.e. $S \in (0, 1)$. Let e be the constrained level of electricity associated with periodic blackouts, $0 \leq e < e^*$. Thus, the constrained cost function is given as:

$$LnC_c \quad = \quad lnC_c(P_k, P_l, P_m, P_e, P_n, \bar{e}) \tag{1.5}$$

A risk neutral firm minimizes the expected cost function of producing a given amount of $\bar{Q}$,

$$ElnC(\bar{Q}) = SlnC_c(\bar{Q}) + (1-S)lnC_u(\bar{Q}) \tag{1.6}$$

The partial derivative of cost in equation (1.6) due to a change in electricity unreliability measures the effect of electricity unreliability on a firm's production cost,

$$\frac{\partial E(lnC)}{\partial S} = lnC_c(\bar{Q}) - SlnC_u(\bar{Q}) > 0 \tag{1.7}$$

The effect of blackouts on the expected value share (V_{shxi}) can be analyzed by taking partial derivatives of the equation (1.4) with respect to S. The price of electricity is not entered in the constrained cost function because of constraint on its availability.

$$\frac{\partial V_{she}}{\partial S} = \frac{\partial^2 lnC}{\partial P_e \partial S} = \frac{\partial lnC_c}{\partial P_e} - \frac{lnC_u}{lnP_e} = -\frac{lnC_u}{lnP_e} < 0 \tag{1.8}$$

A firm's response to power outages can be analyzed by critically examining the response of input value shares due to changes in electricity unreliability, S.

One of the most common strategies that firms adopt to cope with power outage is self-generation of electricity. This would result in an increased use of non-electric energy. This implies that non-electric energy substitutes for electricity from the public grid.

$$\frac{\partial V_{shn}}{\partial S} = \frac{\partial^2 lnC}{\partial P_n \partial S} = \frac{\partial lnC_c}{\partial P_n} - \frac{\partial lnC_u}{\partial lnP_n} > 0 \tag{1.9}$$

Another response to power outage is outsourcing production of electricity-intensive goods. During a period of power outages, a firm may decide to purchase electricity-intensive intermediate inputs rather than producing them from raw materials. In this case, outsourcing could result in reduced use of labor, capital, and non-electric energy. This is given as;

$$\frac{\partial V_{shm}}{\partial S} = \frac{\partial^2 lnC}{\partial P_m \partial S} = \frac{\partial lnC_c}{\partial P_m} > \frac{\partial lnC_u}{\partial lnP_m} \tag{1.10}$$

Lastly, a firm may respond to electricity outages by improving its overall energy efficiency. This would likely cause the share of capital to increase while causing that of electricity and non-electric energy inputs to decline.

$$\frac{\partial V_{shk}}{\partial S} = \frac{\partial^2 lnC}{\partial P_k \partial S} = \frac{\partial lnC_c}{\partial P_k} > \frac{\partial lnC_u}{\partial lnP_k} \tag{1.11}$$

Thus, based on the above theoretical discussions, this study tests the following hypotheses proposed by (Fisher-Vanden et al., 2015).

H1: Power outage decreases the productivity of a firm

Power outages affect production activities in several ways, eventually having a negative effect on productivity. A discontinuous supply of power interrupts the production process, causing productive resources to be idle. Power outages also force firms to invest in generators, which is an additional cost for a firm. Even when firms' backup their electricity demand by investing in generators, they may continue to suffer losses because of their inability to completely backup their electricity load.

H2: Self-Generation

Due to the nature of their business activity, some firms are more vulnerable to power outages than are others. Even within a given firm, some functions of the business are more vulnerable to power outages than are others, so that an outage of a given duration may cause large losses in certain parts of the business, while other parts may be left virtually unaffected. Thus, to avoid such losses, firms have an incentive to act by self-generating that would mitigate some, if not all, of the damage caused by power outages.

H3: Outsourcing

Production of intermediate inputs, especially those that are electricity-intensive, is challenging for a firm during a period of power outages. It would be optimal for a firm to purchase these inputs rather than to produce them in-house. It is rational to expect that firms outsource the production of electricity-intensive intermediate goods during a period of power outages. This, in turn, negatively affects the productivity of a firm because, when a firm is substituting materials for electricity, it is forced to shift from making to buying these intermediate inputs.

H4: Improved energy-consumption efficiency

Firms may also respond to electricity outages by improving their overall energy-consumption efficiency. This could be possible by selectively utilizing the most electricity-efficient method of production, in addition to investing in electricity-saving technologies. This would be a rational mitigation strategy if public authorities promote energy-efficiency policies and power outage takes the form of quota rationing

1.4 Related Literature

Many empirical studies have tested the impact of power outages on firm performance, (for instance, Abotsi, 2015; Alam, 2013; Nyanzu and Adarkwah, 2016; Scott et al., 2014). In testing the impact of power outages on firm performance, most empirical studies have used a proxy measure of power outage. Alam (2013) and Thomas and Dalgaard (2013) used meteorological satellite data lightning density as an instrument for power outages, while Fisher-Vanden et al. (2015), used industry-level estimates, the ratio of thermal electricity generated to thermal electricity capacity. Allcott et al. (2014) instrumented electricity shortage with shifts in electricity supply from hydroelectric power availability. On the other hand, several studies (for instance, Abotsi, 2015; Adenikinju, 2003; Oseni and Pollitt, 2015, 2013) used a firm-level survey data to study the economic cost of power outages and how this affects firm performance.

Numerous studies have used different techniques to try and estimate the cost associated with power interruptions. For instance, Adenikinju (2003); Bental and Ravid (1982); Oseni and Pollitt (2015); Steinbuks and Foster (2010), inferred outage costs from actions taken by firms. However, this method sometimes provides only an upper or a lower limit on outage cost estimates (Balducci et al., 2002). Other studies, Caves et al. (1992); Pasha et al. (1989), have used survey methods in which firms are asked to report the losses suffered due to outages. This approach is attractive in that it yields the distribution of outage costs across customers. There are also studies, for instance, Castro et al. (2016), that have adopted a production function approach to estimate the cost of power interruptions.

Power outages affect business activities in several ways. However, their impact varies across firms, based on the degree of their vulnerability and the generating capacity of a self-generating firm relative to its own electricity requirements (Oseni and Pollitt, 2015). The cost of power outages also varies across firm size and the type of economic activity that a firm is engaged in. In this regard, Adenikinju (2003); Moyo (2012) found that power interruption is particularly harmful to small firms because they are unable to finance the cost of backup energy. On the other hand, a study by Oseni and Pollitt (2015) showed that larger firms face greater outage loss. They suggested that this is mainly because larger firms use more machine-dependent production processes than do small firms.

The cost of power outages also depends on the nature of the power interruptions that a firm faces. Power outages can be characterized in several dimensions, including duration, frequency, the timing of interruption, and advance notification. Some studies have considered the impact of such characteristics on outage costs. Billinton et al. (1982) and Ontario (1980) reported that firms experience high outage costs initially but that the cost diminishes rapidly as the duration increases. With regards to the frequency of interruptions, business enterprises prefer infrequent long duration interruptions to frequent short duration interruptions (Billinton et al., 1982; Ontario, 1980). Scott et al. (2014) obtained a similar result, showing that frequent power outages are associated with lower firm productivity. Studies on the impact of the timing of power interruptions and advance notifications are limited due to data constraints.

Many empirical studies have been devoted to examining the strategies adopted by firms to reduce the associated costs of outages. The most commonly-adopted strategy has been found to be investment in self-generation (Adenikinju, 2003; Oseni and Pollitt, 2015; Steinbuks and Foster, 2010). Steinbuks and Foster (2010) found that both the incentive to invest in a generator and the capacity of the generator installed are greatly affected by firm size, sector, corporate structure, and export orientation. The incentive to invest in self-generation also depends on firms' degree of vulnerability to power interruption (Oseni and Pollitt, 2015). Due to the nature of their business activity, some firms are more vulnerable to power outage than are others. Ghosh and Kathuria (2014) explained the difference in firms' degrees of vulnerability as transaction-specific costs. They treated electricity provision as a transaction and showed that there is a corresponding transaction cost when a firm faces a power outage. They found that a firm facing high transaction costs has more incentive to invest in self-generation of electricity.

The adaptation strategy adopted by a firm depends partly on the nature of the power interruption. According to Alam (2013), short-run power cut may not induce firms to invest in generators. Fisher-Vanden et al. (2015) also show that Chinese firms do not self-generate electricity during power outages but, "rather, re-optimize among production inputs by substituting materials for energy."

Empirical research on outages in Sub-Saharan Africa (SSA) have focused on estimating the economic cost of power outages. However, it is not clear from these studies whether electricity outages lead to electricity efficiency or force firms to substitute material for electricity. This paper differs from earlier studies in SSA in the following ways. First, a cost function is employed to estimate how power outages affects firms' production costs and to test whether power outages affect either input factor shares or overall productivity and how they affect firms' input utilization. Second, the two rounds of firm-level data are used, which provides for a richer analysis than previous studies in the area.

1.5 Methodology

1.5.1 Data Source and Description of Variables

The major source of data for this study is the 2011 and 2015 WBES on firms operating in Ethiopia. The survey used a stratified random sampling technique, and firms were stratified based on their size, sector, and region. Four regions and two self-administrative cities were selected from nine regional states and two self-administrative cities of Ethiopia. The size stratification is based on the number of permanent full-time workers reported and is defined as: micro (less than five employees), small (5–19 employees), medium (20–99 employees), and large (more than 99 employees). A total of 644 firms were surveyed in 2011. In addition to these 644 firms interviewed in 2011, fresh firms were introduced into the survey, making a total of 848 firms interviewed in 2015.

The empirical estimation for the behavioral response of firms to power outages requires firm-level data on production inputs and the amount spent by firms on factor inputs. In the survey, firms were asked to report their annual expenditures on wages and salaries for workers, intermediate inputs, and electrical and non-electrical energy. All the reported expenditures in local currency have been converted to the equivalent USD using the 2015 market exchange rate.

Using these firm-level data, the input prices are computed by firm and year based on expenditure data. Accordingly, the price of labor (Pl) is computed as the annual sum of wages, salaries, and bonuses divided by the number of full-time permanent workers in the company during the year. The price of capital (Pk) is imputed from a firm's total value added minus its total expenditure on labor, divided by the net book value of its assets.

The price of materials (Pm) for a given specific industry is computed as a composite of the annual industry producer price index weighed by the input-output share for that firm's industry. The input-output shares of a firm based on two-digit Standard Industrial Classification (SIC) codes are obtained from the Social Account Matrix (SAM) of Ethiopia. Firms in the same two SIC classifications face the same material inputs over time. The price of electricity (Pe) is obtained from Ethiopian Electric

Power (EEP), while the price of non-electric (Pn) is obtained from German Agency for International Cooperation. In the WBES dataset, there is no information on the quantity of final output. Thus, the deflated total annual sale by general price is used as a proxy for the final output of a firm.

1.5.2 Descriptive Statistics

Table 1.1: Summary of Input Prices and Input Value Shares

Variable	Description	Mean	Std.Dev.
TC	Total Cost (USD)	271665.5	498520.4
Output(Q)	Deflated annual sales (USD)	408763.7	1957976
Outages(S)	Power outages[1]	0.1357	0.9180
Vshk	Value share of capital (%)	0.0105	0.035
Vshl	Value share of labor (%)	0.1021	0.158
Vshr	Value share of raw material (%)	0.8027	0.030
Vshe	Value share of Electricity (%)	0.0110	0.206
Vshn	Value share of nonelectric input (%)	0.0755	0.11
Pl	Price of labor (per person)	227.02	447.7
Pk	Price of capital	3.916	122.9
Pm	Price of Material	99.16	16.0
Pe	Price of electricity (per KWh)	0.022	0.01
Pn	Price of nonelectric energy	0.911	0.02

Source:Computed based on WBES (2011 and 2015)

Table (1.1) reports summary statistics of the total cost (in USD), deflated annual sales in constant (USD), value share of factor inputs, and input prices for each of the factors of production.

The average factor value shares disaggregated to sectoral level are given in Table (1.2). Material input share is the highest percentage of average value shares across all sectors. All industries use electricity; thus, power interruption affects them either directly or indirectly. The average value share of non-electric energy is greater than is that of electricity. This may be due to non-electric energy being costlier than is the electricity supplied from the public grid and firms resorting to the use of non-electric energy sources during power outages.

Table 1.2: Average Input Value Shares by Industry

	Value share				
Sector	Capital	Labor	Mater.	Elec.	Nonel.
Garments, Leather and Textile	1.56	12.23	79.29	1.11	5.71
Food	0.745	9.64	82.40	1.05	6.15
Metals, Machinery and Equipments	1.568	11.43	80.32	0.71	5.95
Nonmetals, Plastics and Paper	1.234	18.17	71.96	1.17	7.45
Wood and Paper	2.048	17.70	70.87	1.14	8.12
Wholesaler, Retailer and Other Services	1.030	8.56	80.97	1.14	8.29
Electronics, Printing, and Publishing	0.765	10.21	80.75	0.70	7.56
Hotels and Restaurant	0.445	5.05	84.70	0.24	7.56
Transport	0.529	6.34	85.38	0.26	7.46
Construction	0.582	6.54	84.85	0.36	7.65
Chemicals and Others	1.513	11.06	79.08	0.68	7.65

Source:Computed based on WBES (2011 and 2015)

In addition to production data, the empirical estimation requires firm-level measures of power outages. A power outage in this study is measured by the number of days that a firm is without a power supply from the public grid. The total outage time that a firm face is obtained by multiplying the number of outages that a firm faces by the duration of the outages, and the total outage time is converted into days.

Table (1.3) reports summary of power outages both in hours and days per year. In 2011, a typical firm faces average power outage of about 548 hours in a year which is equivalent to about 23 days. The figure has increased to more than 1680 hours in a year during 2015 (about 70 days). Table (1.3) also presents power outages by sector.

1.5.3 Empirical Model

In this section empirical model to be estimated for the analysis of the behavioral response of firms to power outages is presented. The study follows Fisher-Vanden et al. (2015) approach in order to test the hypothesis explained in section 1.3.

Table 1.3: Power Outages by Sector and Over Year

Sector		Outages (Hours/year)		Outages (Days/year)	
		Mean	Std. Dev.	Mean	Std.Dev.
Garments,Leather and Textiles		634.99	559.36	26.45	23.30
Food		1550.25	11252.92	64.59	468.87
Metals, Machinery and Equipments		581.57	623.59	24.23	25.98
Nonmetals, Plastics and Paper		725.64	988.04	30.23	41.16
Wood and Furniture		541.88	496.28	22.75	20.67
Wholesaler, Retailer and Other Services		1314.03	7560.28	54.75	315.1
Electronics, Printing, and Publishing		800.84	978.36	33.36	40.76
Hotels and Restaurant		740.20	884.84	30.84	36.86
Transport		2464.74	16924	102.7	705.2
Construction		536.07	711.1	22.33	29.62
Chemicals and Others		2483.5	14816.72	103.5	617.4
	2011	547.94	634.83	22.83	26.45
Year of Survey	2015	1682.81	10659.87	70.11	444.16
	Overall	1189.31	8041.92	49.55	335.08

Source: Computed based on WBES (2011 and 2015)

The productivity effect of power outages can be estimated through production or cost function; the choice of which depends on relevant exogeneity assumption and statistical grounds. In production function estimation in which factor inputs determine the level of output, inputs quantities are assumed to be exogenous. Whereas in cost function estimation, input prices are assumed to be exogenous. In this study, since a firm level data is used in which the choice of quantity of factor inputs are endogenous and factor prices more likely to be determined in the market, cost function approach is more appropriate to adopt. The translog cost function handles any neutral and non-neutral efficiency differences among firms (observational units in the data). Thus, because of its flexibility in functional form, the study adopts the translog cost function, which is specified as follows:

$$
\begin{aligned}
lnC_{ijkt} \quad = \quad & \alpha_0 lnS_{it} + \alpha_1 lnQ_{it} lnS_{it} + \sum_{j=1}^{5} \beta_j lnP_{ijt} lnS_{it} + \sum_{j=1}^{5} \delta_j lnP_{ijt} + \\
& \frac{1}{2} \sum_{j=1}^{5} \sum_{l=1}^{5} \varphi_{jl} lnP_{ilt} lnP_{ijt} + \kappa lnQ_{it} + \frac{\Lambda}{2} (lnQ_{it})^2 \qquad (1.12) \\
& + \sum_{j=1}^{5} \phi_j lnQ_{it} lnP_{ijt} + \eta_k + \varepsilon_{ijkt}
\end{aligned}
$$

where C_{ijkt} is the total production cost of firm i in industry j that produces output Q_{it} using input j at time t, Q_{it} is annual output of a firm i at time t, P_{ijt} is price of input j at time t for firm i (where j includes capital, labor, material, electricity, and nonelectric energy), η_k is industry fixed effect, ε_{ijkt} is the error term, parameters α_0 and α_1 measures the factor neutral effect of power outages allowing the effect to vary with level of output while β_j measures the factor biased productivity effect of power outages.

Using Shephard's Lemma, the cost share equation for each of the factor inputs can be derived from equation (1.12)[2] as:

$$
Vsh_{ijt} \quad = \quad \delta_j + \beta_j lnS_{it} + \sum_{j} \varphi_j lnP_{ijt} + \phi_j lnQ_{it} + \varepsilon_{ijt} \qquad (1.13)
$$

1.5.3.1 Estimation Strategy

Equations in (1.12) and (1.13) represents a system of equations in which shock to

[2]Even though there are five factors of production in our cost function, the add-up conditions across all factors of production implies the covariance matrix would be non-invertible if all value shares of input are included in the estimation. Thus, the main cost specification is estimated along with four of the cost share equations___ value share for material is dropped. As shown in Greene (2003), the coefficient estimates and standard errors are insensitive to the value share dropped.

factors shares are likely to be correlated across error structure of the model. Since the systems of equations are related to each other through their error terms, there is an efficiency gain by estimating the system of equations jointly. Thus, the above system of equations is estimated by three stage least squares in panel data framework[3].

For the cost function specified in equation (1.12) is to be well-behaved, i.e. exhibits the usual property of symmetry and homogeneous of degree one in input prices, the following restrictions are imposed.

$$\varphi_{jl} = \varphi_{lj}, \sum_{j=1}^{5} \delta_j = 1, \sum_{j=1}^{5} \varphi_{jl} = \sum_{j=1}^{5} \varphi_{lj} = \sum_{j=1}^{5} \phi_j = 0 \tag{1.14}$$

The impact of power outages on firm's cost of production can be truly measured only if power outage is exogenous in our model. However, there are a number of reasons that outage is endogenous in this model. Outages can be correlated with factors influencing firm's production cost/productivity such as location, industry compositions and prevailing economic conditions in the country. There is also a possibility of measurement error in power outages because of subjectivity in reporting. In order to address the endogeneity and measurement error, the study utilized variation in hydro- electric generation as instrumental variable in the cost function estimation.

Electricity from hydro power shares more than 87% in Ethiopia and its electricity generating capacity depends on rain fall. The country has faced major electricity shortages in periods of low recorded rain fall (Ethiopian Electric Power, 2015). This shows variation in electricity generation majorly depends on rain fall and it affects firms' production cost only through outages. Thus, variation in hydro elec-

[3] To insure the estimation is invariant to the choice of deleted value share equation, the three stage least square is iterated over the covariance matrix and parameter estimates (see Berndt (1991, pp 474-475)

tricity generation is a good candidate to be instrumental variable for power outages. Variation in hydro generation is measured as the deviation from the mean annual generation over the period of 2011 -2015.

Thus, using variation in hydro generation as instrument in the main specification of translog cost function in equation (1.12), the reduced form regression of power outages on variation in hydro generation and other explanatory variables of the model in equation (1.12) is given by:

$$\begin{aligned} lnS_{ijtk} &= \theta H_t + \theta_1 lnQ_{it}H_t + \sum_j \tau_j lnP_{ijt}H_t + \sum_j \varphi_j lnP_{ijt} + \\ &\quad \frac{1}{2}\sum_j \sum_l \vartheta_{jl} lnP_{ilt} lnP_{ijt} + \psi lnQ_{it} + \\ &\quad + \frac{\Delta}{2}(lnQ_{it})^2 + \sum_j \upsilon_j lnQ_{it} lnP_{ijt} + \mu_k + \varepsilon_{ijtk} \end{aligned} \tag{1.15}$$

This is estimated by three stage least square along with equations in (1.12)-(1.13) imposing restrictions in equation (1.14).

The marginal cost and a change in total cost of production due power outages can be computed from the main equation in (1.12). Taking the first order derivative of cost function with respect our measure of power outages,

$$\frac{\partial C_{it}}{\partial S_{it}} = \frac{\alpha_0 C_{it} + \alpha_1 lnQ_{it}}{S_t} + \sum_{j=1}^{5} \beta_j \frac{lnP_{ijt}}{S_t} \tag{1.16}$$

Where $j = K, L, M, E, N$

The first term represents the factor neutral effect while the second term is the factor biased effect. The overall effect depends on the combination of the two effects. The change in total cost of production due to change in power outages is thus, computed using equation (1.16).

1.5.3.2 Tests on self-Generation

The evidence for self-generation can be tested from the model specified in equation (1.12). For the self-generation hypothesis to hold, as stated above, interaction of power outages and electricity should be negative and that of non-electric energy interacted with power outage be positive.

In addition to this, a further test on self-generation is made by estimating a separate regression of generator ownership (indicator of self-generation) on power outages and other firm characteristics. For this issue, the study adopted Reinikka and Svensson (2002) approach, recently employed by (Steinbuks and Foster, 2010).

A firm adopt a generator if the benefit to a firm from adopting is greater than other options available to it. Thus, the decision to invest in backup energy (adopting generators) by a firm can be modeled using a panel binary choice model.

$$y_{it}^* = x_{it}\beta + \varepsilon_{it}, \; i = 1, 2..N; t = 1, 2, ...T \tag{1.17}$$

where $\varepsilon_{it} = \alpha_i + u_{it}, u_{it} \backsim N(0, \delta_u^2); \alpha_i \backsim IIN(0, \delta_\alpha^2)$

From the latent variable model in equation (1.17) and the assumptions given, the probability that a firm invest in self-generation is given as:

$$Pr(y_{it} = 1) = Pr(y^*_{it} > 0/x_{it}) = P[\varepsilon_{it} > -(x'_{it}\beta)/x_{it}] \quad (1.18)$$
$$= \Phi(x'_{it}\beta)$$

where y_{it} is the probability that firm i invests in self-generation, Φ is the standard normal distribution function, x_{it} is a vector of controls including frequency of power interruptions and other firm characteristics that affects firm's decision to invest in self-generation.

The usual assumption to estimate the model in equation (1.17) is the unobserved individual heterogeneity term, α_i is independent of x_{it} . However, it is unrealistic in many cases to assume that the time invariant unobserved individual heterogeneity α_i is independent of the observable variables in x_{it} (Mundlak, 1987; Chamberlain, 1982). As indicated in Mundlak (1987); Chamberlain (1982), it is possible to estimate more precise parameter of the model in equation (1.17) by allowing for correlation between α_i and x_{it}. This is done by including the time average of variables in x_{it} as additional regressors in the model. This works by specifying the unobserved heterogeneity α_i as follows:

$$\alpha_i = \psi + \pi'\bar{x}_i + \nu_i \quad (1.19)$$

where $\nu_i \sim IIN(0, \delta^2_v)$ and $\bar{x}_i$ is the average of time varying variables in the vector x_{it}

The estimation of the models in (1.18) and (1.19) by maximum likelihood method is called a correlated random effect model (Wooldridge, 2010).

1.6 Results

The first column of Table (1.4) report results based on the system of equations in (1.12) and (1.13) along with equation (1.15). Because of the adding-up restriction in equation (1.14), only four of the five value share equations in (1.13) are linearly independent[4]. Thus, the value share of material is dropped from the system of value share equations to have an invertible covariance matrix. In all estimations, power outages and its interactions with input prices and output are instrumented by variations in hydro generations as represented in equation [5] (1.15).

The results[6] show that power outage leads to substitution among the factors of production. More specifically, a power outage results in increased use of capital, materials, and non-electric energy sources while the use of labor and electricity decreases. For instance, every one standard deviation increase[7] in a power outage leads to an increase in the cost share of capital, material and non-electric energy sources of 0.022, 0.032, and 0.040 standard deviations, respectively. The same one standard deviation increment in a power outage leads to a decrease in the cost share of labor and electricity of 0.011 and 0.003 standard deviations, respectively.

Referring to the research hypothesis in section 1.3, the result obtained supports the decreased productivity effect of outage and self-generation as a coping strategy to mitigate the associated outage cost. The productivity effect of power outage (H1) depends on the factor-neutral and factor-biased effects, which is the same as testing

[4]If there are n value share equations, only n-1 of them are linearly independent because value shares always sum to unity (see Berndt (1991, pp 371-372).

[5]Relevance test of the instrument shows a variation in hydro generation is significant and positively explains the power outages even though some of the interaction variables found to be insignificant. In addition, the instrument passed Stock and Yogo weak test as the Wald test critical values pertaining to Stock and Yogo weak instrument test ranges from 5.5 to 16.4 which is less than the first stage F-statistics (See Appendix Table A.4).

[6]Full coefficient estimates of main specification is reported in Appendix Table A.1

[7]The variables of the models are standardized before estimation around their arithmetic mean, as $x^* = (x_i - \bar{x})/s_i$, $\bar{x}$ where is mean of the variable in the sample, and s_i is the standard deviation. According to Walsh (cited in Bring (1994) standardized coefficients can be used to assess relative importance of each of explanatory variables in predicting the dependent variable.

the significance of $\alpha_0 = \alpha_1 = 0$ and $\beta_j = 0$ in the main cost specification in equation (1.12).

Table 1.4: Cost of Power Outages

	Main specification		CRS		No interaction	
	Coef.	Std.Dev	Coef.	Std.Dev.	Coef.	Std.Dev.
lnPklnOutage	0.022***	0.024	-0.0005	0.0201	-0.0004	0.0201
lnPlnlOutage	-0.011	0.016	-0.0221	0.0100	-0.0192	0.0161
lnPelnOutage	-0.003*	0.002	-0.0038***	0.0024	-0.0036*	0.0024
lnPnlnOutage	0.040**	0.020	0.0378***	0.0200	0.0355*	0.0200
lnPmlnOutage	0.032**	0.018	0.0340**	0.0180	0.0366**	0.0180
lnOutputlnOutage	-0.037*	0.022				
lnOutput	0.669***	0.101	1		0.6844***	0.1014
lnOutage	0.027*	0.016	0.020***	0.020	0.0212	0.0165

*** P≤0.01, **0.01< P≤0.05, * 0.05<P≤0.1. The dependent variable of the model is the log of cost by firm and year. Add up and symmetricity restrictions are imposed, value share for material inputs is dropped to have invertible covariance matrix and the estimation is made for the main specification in equation (12) along with cost shares of the four factors of productions. In the second column, constant returns to scale is imposed and coefficient associated interaction of output with outages is set to zero. The third column does not include the interaction of output with outages. In all cases, the restrictions imposed does insignificant changes compared to the result from the main specification in column1.

The results show that the null hypothesis that power outage has no factor-neutral or factor-biased effects is rejected in favor of an alternative hypothesis. The net effect of power outages on a unit cost of production depends on the combination of this factor-neutral and factor-biased effects. The positive factor-neutral effect of outage indicated by the positive coefficient of outage alone shows that a one standard deviation increment in power outages increases firms' production costs by 0.027 standard deviations. This effect diminishes with the output level of the firm, as indicated by the negative interaction of output and power outage. This indicates that a power outage negatively affects a firm's productivity and that the effect on small firms is more pronounced, which is consistent with the first hypothesis of the study. This is mainly because small firms face financial constraints in adapting to power outages.

Given the negative impact of a power outage, as confirmed by the first hypothesis of the study, firms adopt different strategies to reduce the resulting cost of power outages. The second hypothesis relates to self-generation of electricity as a coping strategy to mitigate the cost of a power outage. The result obtained shows that an increase in power outage leads to a decline in cost share of electricity, while the cost share of alternative energy sources increases. This is in line with the self-generation hypothesis, in which power outages induce firms to invest in self-generation when the supply of power from the public grid is not available. To examine how self-generation varies across firm size and other firm characteristics, a separate regression of a self-generation indicator on firm characteristics and a measure of power outage are made and discussed in the next section.

The third and fourth hypothesis of the study relate to the alternative coping strategies that a firm adopts. There is evidence of an increment in the cost share of materials due to increased outage intensity. This is indicated by a significant and positive coefficient of material input. An increment in the cost share of material supports the outsourcing hypothesis; firms are induced to shift from making to buying some of their intermediate goods. However, for this hypothesis to hold, the estimated coefficient of electricity and non-electric energy sources should be negative. On the contrary, the coefficient of non-electric energy source is positive. Thus, the result does not support the outsourcing hypothesis. The result obtained also does not support the improved energy-efficiency hypothesis, because there is no observed decline in the cost share of non-electric energy in the result obtained. The short time span of the data used in the study, however, may not be enough to show a firm's capital adjustment.

1.6.1 Industry Heterogeneity

To account for heterogeneity among sectors in responding to power outages, the system of equations in (1.12) and (1.13) is estimated by 3SLS separately for each sector[8]. A significant response to a power outage in electricity share is observed in the Food, Wholesaler, and Construction sectors. The negative coefficient associated with the interaction of electricity and power outages in these sectors shows that power outages reduce the cost share of electricity. The interaction coefficient of outages with electricity and material inputs is positive and significant for many of the sectors. This shows that the cost share of material input increases in response to power outages. However, revisiting the earlier hypothesis, the result obtained is noisy.

1.6.2 Further Test on Self Generation of Electricity

As a further test of the self-generation hypothesis, a separate estimation is made using equations (1.18) and (1.19). Two measures of self-generation indicators are used: the share of electricity consumption coming from self-generation and the indicator variable of self-generation, which is a binary outcome. For firms that do not invest in self-generation, the share of electricity coming from self-generation is zero. Thus, the dependent variable is zero for a substantial number of firms in the sample. For this model, Tobit is assumed[9], as it is suited to model a problem of this nature Verbeek (2004). For the self-generation indicator, a probit decision adoption is assumed. The measure of power outage used in both specifications is the frequency of power interruption that a firm faces in a year. Determinants of firm decision to invest in self-generation are estimated using the regression approach stated in equations 1.17 and 1.18. Both pooled probit and Correlated Random Effect Probit (CREP) are estimated. The likelihood ratio test on the coefficient of ρ, which

[8] The result is reported in A.3

[9] see Appendix 1.8.2 for the Tobit model specifications

captures unobserved heterogeneity among firms, is significant. This indicates the importance of capturing unobserved firm heterogeneity in the model which indicates that CREP is more appropriate.

The positive and significant coefficient of a variable ownership shows that foreign-owned firms are more likely to own generators compared to domestically owned firms. Variable size in the model shows the number of full-time permanent workers in the company. The estimated coefficient of the variable is positive and significantly explains generator ownership. This indicates that larger firms are more likely to invest in generators compared to small firms.

Table 1.5: Test for Self-Generation

Generator Ownership (=1 if Own)			Share of self-generation		
Variable	Coef.	Std.Dev	Variable	Coef.	Std.Dev.
Exporter (=1 if export)	0.173	0.188	Exporter	0.404	0.350
Ownership (=1 if foreigner)	0.483**	0.201	Ownership	0.867**	0.349
Region (=1 if capital city)	0.530***	0.123	Region	1.097***	0.230
Manufacturing	-0.121	0.210	Manufac.	-0468	0.404
Retail	-0.181	0.174	Retail	-0.298	0.349
Large	0.480***	0.151	Large	0.348	0.296
Medium	0.175*	0.262	Medium	0.673	0.490
lnAge	0.134	0.067	lnAge	0.438***	0.140
lnSize	0.205***	0.077	lnSize	0.289***	0.130
ln (Freq.Inter)	0.162**	0.071	ln(Fre.Inter.)	0.392***	0.133
ρ	0.319	0.111	ρ	0.214	0.090
Waldχ^2(21)=87.86 Prob>χ^2=0.00 Waldχ^2(21) = 200.78 Prob> χ^2= 0.000					
LR test of $\rho = 0$:$\bar{\chi}^2(01) = 7.47$ Prob $\geq \bar{\chi}^2$= 0.003					

*** $P \leq 0.01$, **0.01< P≤0.05, * 0.05<P≤0.1. ln(Freq.Inter) shows log of number of power interruptions. Two indicators of self-generation are used, generator ownership; estimated probit model and the share of electricity from generator; estimated by Tobit model.

The variable of interest, the frequency of power interruptions, is both positive and significant under both regressions. More specifically, frequent power interruption increases the likelihood that firms invest in a generator and, hence, increases the share of electricity coming from generators. Revisiting the earlier hypothesis, this is in line with the self-generation hypothesis.

1.6.3 Regularity Conditions

For the estimated cost function to be consistent with economic theory, it is important to test if the estimated translog cost function satisfies certain regularity conditions, mainly monotonicity and concavity. Monotonicity is tested by the sign of the predicted cost shares for each factor input at each observation. The result shows (see A.2) that there are observations with negative predicted cost shares, implying that cost is decreasing in the price of that input at that observation. However, this occurs at relatively few points compared to the size of observation in the data.

For the cost function to be concave in input prices, the own price elasticity for each factor input must be negative. This implies that the demand for factor input decreases as the price of that input increases. This is confirmed by the estimated own-price elasticities of inputs given along the main diagonal of the lower panel of A.2. This is consistent with microeconomic theory, and the estimated own price elasticities have the correct negative sign. Each pair of cross-price elasticity of input have the same sign, however, they differ in magnitude because they depend on input value shares. This satisfies the symmetricity condition imposed.

1.6.4 Costs of Power Outages

In this section, the marginal and total costs of power outage are computed using equation (1.16) and the estimated factor-neutral and biased coefficients reported in Table 1.4. The mean value of all the explanatory variables, including power outage, is used for the marginal cost computation.

The overall marginal cost is \$1,625, of which the factor-biased effect is \$2,592, and the factor-neutral effect is -\$9,67. This shows that, in substituting one factor of production for the other in response to power outages, the overall productivity losses from the marginal increase in power outage offsets the marginal gains from a marginal increase in outage. The factor bias effect is decomposed into each of the factor inputs, with a shift to non-electric energy sources in response to power outages increasing the cost by $658, while capital and material increase the cost by $761 and $2,628, respectively. The decreased use of electricity and labor partially offsets the increased cost of production due to the shift to material and non-electric energy sources.

Table 1.6: Marginal and Total Cost due to Outages (in USD)

Components of cost	Marginal cost of outages	Cost of outages (2011-2015)	% of aggregate cost (2011-2015)
Factor neutral	-$986	-$45719	-8.6%
Factor biased	$2592	$122549	23.2%
Capital	$761	$35980	6.8%
Labor	-$963	-$45530	-8.6%
Electricity	-$492	-$23261	-4.4%
Non-electric	$658	$31110	5.9%
Material	$2628	$124251	23.5%
Net effect	$1625	$76830	14.5%

The first column calculates marginal cost of power outages based on estimated coefficients and mean values of explanatory variables. In the second, total cost of power outages due to the actual change in power outages between 2011 and 2015 is computed. The last column divides the total cost due to power outages in the second column by firm's aggregate cost.

The second column of Table (1.6) reports the total cost due to the actual change in the power outage. To calculate this, the marginal cost of outage reported under the first column is multiplied by the actual change in the average duration of power outages from 2011 to 2015. The overall total cost has increased by $76,830 which is approximately 15% of a firm's aggregate[10] cost. Of this total, material input takes the leading share, being approximately 23.5% of the aggregate cost.

The result obtained has similarities to the findings of Fisher-Vanden et al. (2015) on the effect of power outages on firm productivity. The increase in firms' cost of production due to power outages is approximately 15%, higher than the figure obtained by Fisher-Vanden et al. (2015) for China. This may be due to the differences

[10] Aggregate cost is obtained by taking the average total cost of production for each year and aggregating over a year

in the causes and severity of power outages between China and Ethiopia. However, unlike the findings of Fisher-Vanden et al. (2015), the results obtained in this study do not support the outsourcing hypothesis. On the contrary, firms in Ethiopia self-generate electricity as an adaptation strategy to cope with power outages. Firms are willing to invest in self-generation if the power outages will extend into the future, while short-term power outages induce firms to outsource part of their production (Alam, 2013). The results obtained thus suggest that, in a country like Ethiopia, where power outages are both frequent and prolonged, self-generation emerges as the strategy that firms adopt in mitigating the cost of outages. However, a cross-country comparative study on the nature of power interruptions and firm strategies are required to generalize this finding.

1.7 Conclusion and Policy Implications

1.7.1 Conclusions

This study employed the World Bank Entreprise Survey data for 2011 and 2015 to examine the characteristics of power outages and how firms in Ethiopia respond to this power interruptions. The economic cost of power outages and firms' behavioral responses to power interruption were examined using the translog cost function.

The findings show that there is factor substitution in response to power outages. The factor shares of electricity and labor declined in response to power outages while that of materials and non-electric energy increased. Firms in Ethiopia were found to self-generate electricity to mitigate the cost of power outages. From the result obtained, there is no evidence supporting the outsourcing and improved energy hypothesis. Power outages affected firms' productivity negatively, and the overall total cost due to outage increased by approximately 15% of firm's aggregate costs from 2011 to 2015. This effect varied negatively with output level, suggesting that outage is particularly costly for small firms.

1.7.2 Policy Implications

The following policy implications may emerge from the results obtained. The marginal cost of a power outage was found to be significant, and firms were found to self-generate electricity to cope with the power outages. This suggests that there is a market for investing in the power system, including building more power plants to ensure reliable electricity supply. One means could be to remove subsidies and introduce optimal tariffs to recover the costs of grid investment. This, in turn, could help attract international and domestic private investors to the power sector[11].

Generator ownership and the share of electricity coming from self-generation were found to be positively correlated with firm size. This is mainly because small and micro enterprises lack the resources to invest in self-generation of electricity. Under this circumstance, shared generators could help small and micro enterprises access and utilize backup power during power outages. Thus, in the short term, the government should facilitate the formalization of shared generators, particularly for industrial parks, to avoid coordination challenges among firms.

[11] Currently, due to government subsidies, customers pay only 67% of the cost of electricity. Revising the electricity tariff and hence attracting investors to the sector may need a regulation. Therefore, there should be electricity regulation that ensures and encourages the participation of private investors to the sector.

1.8 Appendix

1.8.1 Additional results from chapter one

Table A.1: Full Coefficient Estimates of Main Specification

Variable	Coef.	Std. Err.	P-Value	Variable	Coef.	Std.rr	P-value
lnPklnOutage	0.0220	0.024	0.352	lnPk_k	0.1834	0.041	0.000
lnPllnOutage	-0.0112	0.016	0.513	lnPl_k	-0.1742	0.032	0.000
lnPelnOutage	-0.0034	0.002	0.075	lnPm_k	-0.0251	0.030	0.398
lnPnlnOutage	0.0401	0.020	0.045	lnPn_k	0.0773	0.032	0.017
lnPmlnOutage	0.0321	0.018	0.072	lnPe_k	0.0102	0.010	0.293
lnOutputlnOutage	-0.0370	0.022	0.098	lnOutput_k	0.3132	0.041	0.000
lnOutput	0.6692	0.101	0.000	lnOutage_k	-0.0391	0.028	0.164
lnOutage	0.0272	0.016	0.102	lnPk_l	-0.5091	0.058	0.000
lnPkPk	-0.0091	0.007	0.200	lnPl_l	0.3493	0.045	0.000
lnPlPl	0.0096	0.006	0.110	lnPm_l	-0.2812	0.042	0.000
lnPelnPe	0.0033	0.001	0.029	lnPn_l	-0.1132	0.045	0.014
lnPmPm	0.0038	0.003	0.331	lnPe_l	-0.0542	0.014	0.000
lnPnPn	-1.5970	1.740	0.000	lnOutput_l	0.3612	0.058	0.000
lnOutputlnOutput	0.1359	0.045	0.003	lnOutage_l	-0.0840	0.039	0.030
lnPkPl	-0.0273	0.009	0.003	lnPk_e	-0.5014	0.533	0.347
lnPkPe	-0.1001	0.051	0.053	lnPl_e	-2.1601	0.416	0.000
lnPkPm	0.0149	0.006	0.031	lnPm_e	-1.3351	0.385	0.001
lnPkPn	0.2510	0.407	0.537	lnPn_e	0.4120	0.414	0.320
lnPlPe	0.0754	0.056	0.181	lnPe_e	0.6250	0.128	0.000
lnPlPm	-0.015	0.007	0.038	lnOutput_e	0.7712	0.529	0.145
lnPlPn	-1.258	0.568	0.027	lnOutage_e	-0.2834	0.361	0.432
lnPePm	0.0240	0.044	0.589	lnPk_n	0.0082	0.004	0.047
lnPePn	-0.3850	2.642	0.884	lnPl_n	-0.0073	0.003	0.821
lnPmPn	-2.3261	0.316	0.000	lnPm_n	-0.0015	0.003	0.601
lnPklnOutput	0.0392	0.065	0.548	lnPn_n	0.0163	0.003	0.000
lnPllnOutput	0.0266	0.029	0.361	lnPe_n	0.0016	0.001	0.094
lnPelnOutput	0.0246	0.008	0.006	lnOutput_n	-0.0071	0.004	0.054
lnPmlnOutput	-0.1831	0.023	0.000	lnOutage_n	-0.0015	0.003	0.580
lnPnlnOutput	0.0206	0.027	0.446				

Industry fixed effects are not reported

1.8.2 Tobit Model specification

Let y^* be a latent variable observable only for firms with positive amount of invest-

Table A.2: Predicted Cost Shares and price elasticity of inputs

Predicted cost Shares				
Model	Capital	Labor	Electricity	Nonelectric
Main	55	0	0	0
CRS	46	1	0	2
No interaction	59	0	3	0
Cross and own Elasticity of Inputs				
	Capital	Labor	Electricity	Nonelectric
Capital	-0.720	-0.204	0.042	0.055
Labor	-0.290	-0.629	0.277	0.091
Electricity	0.217	0.586	-0.447	-0.350
Nonelectric	0.282	0.379	-0.772	-0.588

ment,

$$y_{it}^* = \alpha_i + x_{it}'\beta + \varepsilon_{it} \tag{1.20}$$

where $\alpha_i \sim N(0, \delta_\alpha^2)$ and $\varepsilon_{it} \sim N(0, \delta_\varepsilon^2)$. $y_{it} = y_{it}$ if $y_{it}^* > 0$ and $y_{it} = 0$ if $y_{it}^* \leq 0$

Since the share of electricity from self-generation is zero for firms that don't invested in self-generation, the dependent variable y_{it} which represents the share electricity from self-generation is left censored at zero. This can be written as:

$$y_{it} = \begin{cases} \alpha_i + x_{it}'\beta + \varepsilon_{it} & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* \leq 0 \end{cases} \tag{1.21}$$

The above model can be written in the following way

Table A.3: Industry specific cost effect of power outages

Table A.3: Industry Specific Cost Effect of Power Outages

Industry	Lnoutagesln output	lnoutput	Lnoutage	lnPmlnoutages	Lnpnlnoutages	lnPElnoutages	Lnpllnoutages	lnpklnoutages
Garment	-2.245	0.0423	0.1022	0.153***	-3.5972	-0.161	0.1128*	-0.0407
	(2.402)	(0.480)	(0.174)	(0.047)	(3.028)	(0.303)	(0.066)	(0.041)
Food	-2.13**	0.206	0.086	0.21***	-2.790	-0.438**	0.086*	-0.11***
	(1.117)	(0.27)	(0.09)	(0.052)	(2.458)	(0.238)	(0.51)	(0.045)
Metals	-2.641	-0.304	0.333	0.065	5.805	-0.305	0.061	-0.047
	2.215)	(0.565)	(0.21)	(0.046)	(4.026)	(0.365)	(0.059)	(0.060)
Non metals	-1.029	0.549	-0.014	0.058	5.358*	-0.141	0.17***	-0.069
	(1.846)	(0.56)	(0.18)	(0.049)	(3.053)	(0.269)	(0.063)	(0.060)
Wood	0.944	1.582	-0.344	0.146**	-1.240	-0.425	-0.070	-0.121
	(3.837)	(1.063)	(0.39)	(0.065)	(5.004)	(0.688)	(0.163)	(0.091)
Wholesaler	-1.191	0.53**	-0.074	0.17***	-5.9***	-0.38***	0.046*	-0.019
	(1.124)	(0.284)	(0.10)	(0.021)	(1.848)	(0.107)	(0.027)	(0.022)
Electronics	1.287	0.956	-0.120	0.0184	6.595*	-0.302	0.158**	-0.072
	(4.043)	(0.236)	(0.38)	(0.113)	(3.743)	(0.221)	(0.071)	(0.055)
Hotels	-2.899	0.233	0.076	0.20***	-4.710	-0.269	0.040	-0.076
	(2.099)	(0.391)	(0.12)	(.068)	(3.717)	(0.236)	(0.088)	(0.063)
Transport	1.881*	0.901***	-0.25*	0.25**	-1.372	-0.340	0.174**	-0.115*
	(2.164)	(0.352)	(0.13)	(0.063)	(5.386)	(0.332)	(0.088)	(0.063)
Construction	-4.4***	-0.058	0.29**	0.042	6.759	-0.700*	0.123	-0.100
	(1.465)	(0.336)	(0.14)	(0.068)	(5.101)	(0.382)	(0.107)	(0.102)
Chemicals	-1.622	0.641***	-0.040	0.21**	-8.354*	-0.292	-0.017	-0.149**
	(1.488)	(0.275)	(0.09)	(0.081)	(4.221)	(0.301)	(0.108)	(0.073)

Figures in brackets are standards errors. * Significance at 10%, ** significance at 5% and **** significance at 1%. Estimation by 3SLS.

$$Pr(y_{it} \quad > \quad 0) = 1 - \Phi(-\frac{\alpha_i + x'_{it}\beta}{\delta_\varepsilon}) \tag{1.22}$$

Table A.4: Test of Instrument Relevance

Variable	Coef.	Std.Err		
Hvar	0.00530*	0.0024513		
lnPkHvar	0.00024	0.0002276		
lnPlHvar	-0.00041	0.0002788		
lnPeHvar	0.00536***	0.0011781		
lnPmHvar	0.00065**	0.0001883		
lnOutputHvar	0.00026	0.000191		
Stock and Yogo weak				
	10%	15%	20%	25%
2SLS size of nominal 5% Wald test	16.38	8.96	6.66	5.53
First stage F stat	24.68			
Prob.>F	0.00			
H_0: Instrument is weak				

Price of non-electric energy is omitted because of collinearity. Only the interaction of instrumental variable with input prices and output is reported

where y_{it} is capacity of firm's generator measured by a share of electricity coming from self-generation, x_{it} is a set of explanatory variables including frequency of power outages, Φ denotes the standard normal distribution function, δ_ε is the standard error of normally distributed error term, ε_{it}.

2 Firm Performance Under Infrastructure Constraints: Evidence from Sub-Sahara African Firms

Abstract

The poor business environment mainly poor infrastructure is found to has paramount importance in explaining Africa's disadvantage relative to other similar countries. To cope with this poor supply of electricity, firms adopt different mechanisms to reduce the resulting effects. The commonly adopted coping strategy is investment in self-generation of electricity. This study examined the role of investing in self-generation in mitigating the outage loss and evaluated the outage loss differential between firms that invested in self-generation and those that didn't using WBES data collected from firms operating in 13 SSA countries. The result obtained shows that, though self-generation has reduced the amount of outage loss for firms that have invested in self-generation, these firms continue to face higher unmitigated outage loss compared to firms without such investment. In spite of this, firms that have invested in self-generation would have incurred 36%-99% more than their current outage loss if they don't engaged in self-generation. Similarly, firms that didn't invest in self-generation would have reduced their outage loss by 2% - 24% if they had engaged in self generation. The study thus, recommended a differential supply interruption to be followed by public authorities based on firms' degree of vulnerability to power interruptions.

Keywords: Power Outages, Self-generation, Firm, Sub-Sahara Africa

2.1 Introduction

The business environment in which a firm operates –encompassing features of legal and regulatory services, infrastructures, financial and institutional systems of the country– has an important impact on firm performance. These business environments also called 'investment climate' varies across regions and countries. For this matter, empirical studies aimed at investigating the impact of business climate on firm outcomes proceed both at a firm and country level. Cross-country empirical works show strong evidence that underdeveloped business environment is associated with a poor investment, employment, and growth[1].

A poor business environment mainly poor infrastructure is found to has paramount importance in explaining Africa's disadvantage relative to other similar countries. According to the study by (Iacovone et al., 2014; Harrison et al., 2014), African firms lead in productivity levels and growth when controlling for the political and business environments. However, without considering these factors, African firms were found to have a significant disadvantages across all performance measures. This indicates that Africa's disadvantages arise from its weak business environment, mainly poor public infrastructure and lack of access to finance.

Recent empirical studies on Sub-Sahara Africa (SSA), (Iacovone et al., 2014; Scott et al., 2014; Cissokho and Seck, 2013), also show that poor infrastructure mainly poor supply of electricity is negatively related to firm productivity, efficiency and growth[2]. This poor quality of electricity service can drive up firms' cost of production[3] and bias their technological choices. It also affects firms' incentive to make an investment decision. According to Abeberese (2016), firms are not willing to locate their business in the area where the supply of electricity is highly unreliable.

[1]see Iacovone et al. (2014); Escribano et al. (2009); Harrison et al. (2014)

[2]see also Steinbuks and Foster (2010); Nyanzu and Adarkwah (2016); Oseni and Pollitt (2015); Adenikinju (2003)

[3]see Fisher-Vanden et al. (2015)

To cope with this poor supply of electricity, firms adopt different mechanisms to reduce the resulting effects. The commonly adopted coping strategy is investment in self-generation of electricity. The decision to invest in self-generation depends on not only reliability power supply but also other firm characteristics such as industry type, firm's power intensity level, and other firm characteristics (Steinbuks and Foster, 2010; Oseni and Pollitt, 2015; Adenikinju, 2003). Firms facing the same outage time may have different incentive to invest in self-generation due to a difference in their degree of vulnerability to power outages. Referring to the sample of firms used in this study, 76% of firms in Senegal own generator which is greater than the percentage of firms owning generator in Ghana (53%)– where power problem is severe compared to that of Senegal (see Figure 2.2). On the hand, in terms of power intensity level, firms in Senegal are more power intensive than firms in Ghana. This is a possible explanation why firm's incentive to invest in self-generation depends not only on the duration of outage but also on the power intensity level of a firm's business activities.

Although investment in self-generation is the common mitigation strategy adopted by SSA firms, it does not always guarantee complete mitigation of outages (Beenstock et al., 1997). The data used in this study described in (Figures 2.1 and 2.2) also reveals that in Nigeria, where about 86% of firms own generator, firms still suffer outage loss of 12%. In this regard, this study asks: Does investment in self-generation help firms in mitigating outage loss and what is the outage loss differential between firms that invested in self-generation and those that didn't?

There is a limited literature with a objective of examining the role of investment in self-generation in mitigating outage loss. Pasha et al. (1989) showed that investment in self-generation reduces the reported cost of power outages in industrial sector of Pakistan but it is impossible to infer outage cost differential between firms that invested in self-generation and those that didn't from their result. Steinbuks and

Foster (2010) compared the cost and benefits of owning generator for Sub-Saharan African firms, however, they didn't consider the role of investing in self-generation in mitigating outage loss. A study by Oseni and Pollitt (2015) is more close to this study. The authors examined outage loss differential between firms that engaged in self-generation and those that didn't using the switching regression.

The switching regression utilized by Oseni and Pollitt (2015) is based on exogeneity assumption of power outages and hence the independence between firm's decision to invest in self-generation and the corresponding outage loss that firms face. However, this assumption may result in selectivity bias. The selectivity bias arises because of the correlation between the outage loss that a firm face and the decision to invest in self-generation. This is because both decision to adopt a generator and the amount of outage loss are determined by firm characteristics, outage time and power intensity of a firm's business activity. This makes the error terms in the outage loss equation and selection equation to be correlated. Ignoring this correlation results in a biased estimates (Maddala, 1993). The endogenous switching regression overcomes this problem because the decision to invest in self-generation is treated to be endogenous. Thus, this study uses endogenous switching regression in a counterfactual framework to examine the role of self-generation in mitigating outage loss and examine outage loss differential among SSA firms that invested in self-generation and those that didn't.

The remaining part of the paper is organized as follows: The following section provides a conceptual framework and research hypothesis. Section 3 presents data source and describes the estimation strategies and the empirical model. Section 4 presents empirical results; while the final section provides conclusions and policy implications drawn from the study.

2.2 Theoretical Model of Firm's Investment in Self-Generation

Firm's decision to invest in self-generation, like other investment decisions, depends on several factors including firm's financial capacity and internal firm decision process. In this section, a theoretical framework on a firm's investment decision based on the Net Present Value (NPV) criterion is discussed.

Since the availability and quality of public electricity are uncertain, a risk-neutral firm decides whether to invest in a generator of size, $G_i > 0$. A firm incurs a fixed cost k for installing a generator and a running cost of μG_i per hour, which is mainly a fuel cost. A firm that has installed an electric generator can ensure a return of φG_i, where $\varphi > 0$ is a generator's productivity.

In a NPV approach to investment decision, all capital costs have to be weighed against the expected future benefits and a firm undertakes an investment with a positive NPV (DeCanio and Watkins, 1998). A firm that invests in a self-generation gets a benefit of a reduced outage loss that the firm would have incurred in the absence of such investment. Given the above information, the firm that invested in a private electricity can reduce the outage loss[4] by $\lambda HQ - \varphi HG_i$, where Q is the total annual sales of the firm in USD, λ is a measure of the degree of vulnerability of the firm's operation to power outages, $0 < \lambda \leq 1$ [5] and H is total outage time in a year [6]. Thus, based on the given cost and benefit of investing in self-generation, the NPV can be determined as:

[4]The amount of outage loss depends on the amount mitigated by adopting generator, even if partial, and total duration of a power outage in a year (H).

[5]The value of $\lambda = 0$ indicates a situation where firm's operation is completely immune to power outages and excluded in this study

[6] In the absence of power interruption, the reported outage loss is assumed to be zero

$$NPV = \sum_{t=1}^{T} \frac{1}{(1+r)^t}\{(\lambda HQ - \varphi HG_i) - C_t^G[\mu G_i,\ k, \phi]\} \tag{2.1}$$

Where t is a year, T is the generator's lifetime, r is the discount rate, k is the fixed cost of generator whereas μG is a running cost, ϕ is financial barriers. Financial barriers indicate among other things whether the firm has easy access to external finance or not.

Based on the above theoretical discussions, the following empirically testable hypothesis is set.

Hypothesis

Firms that invested in self-generation face higher unmitigated outage loss compared to firms without such investment.

Firms that invested in self-generation may continue to suffer higher unmitigated outage loss compared to firms that didn't invest in self-generation. This could be possible if electricity from self-generation is not enough to fully back up firm's electricity load and the firm is highly vulnerable to power outages.

Proof: Consider two firms with an information presented above. Assume further that output is subjected to an hourly outage loss of λQ for firms that invested in self-generation and θQ for firms without such investment. The outage loss function for a firm that invested in a self-generation is given as:

$$L_s = \lambda Q + C^G(\mu G_i, k, \phi) - \varphi G_i) \tag{2.2}$$

where $C^G(.)$ is the cost of investing in self-generation defined in equation (2.1)

The outage loss for firms that didn't invest in self-generation is given by:

$$L_f = \theta Q \tag{2.3}$$

where λ and θ measures the degree to which a firm's business activity is vulnerable to power outage for a firm that invested in self-generation and those that didn't respectively.

Thus, firms that invested in self-generation can face higher outage loss if $\lambda > \theta$ i.e. highly vulnerable to power outages and the mitigating capacity of the generator is small compared the required electricity load of the firm.

2.3 Methodology

2.3.1 Data

The source of data for this study is the World Bank Enterprise Survey (WBES) collected from firms operating in 13 Sub-Saharan African countries[7] for which the survey is conducted between between 2010 and 2016. These countries were selected based on their sample size and the year of a survey conducted. Comparable information using the same survey instruments across all countries are available after 2010. Thus, this study considered only countries for which the survey is available after 2010.

Combining a firm level data for these countries, there are about 5,129 observations in data set. However, there are firms that reported zero outage loss either because firms are immune to outages due to the nature of their business or they have completely

[7]The study covers 13 SSA countries namely: Cameron, Ethiopia, Ghana, Kenya, Mali, Namibia, Nigeria, Senegal, Sudan, Tanzania, Uganda, Zambia and Zimbabwe

backed up their electricity load. After cleaning for these observations, 3029 firms are left in the sample. . The sampling distribution of the data ranges from 119 firms in Namibia and Uganda, about 4% of total sample, to 505 firms in Nigeria which is about 17% of the sample[8].

2.3.2 Variables and Descriptive Statistics

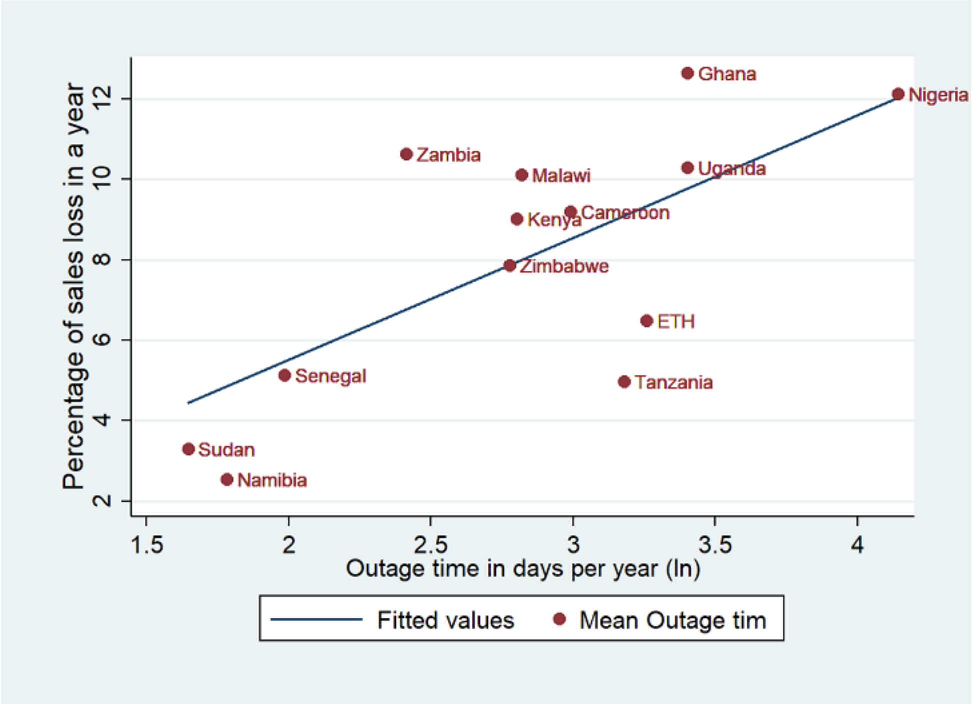
Self-generation (G) – In the WBES, firms were asked to report whether they own generators or not during the survey period. Firms that own generator were asked to report the share of electricity coming from self-generation (G_{sh}) as a percentage of their total electricity load. The percentage of electricity from self-generation is observed only for firms that have invested in self-generation and it is censored at zero from left. Table (2.1) presents the descriptive statistics of investment in self-generation and other variables used in the study and Tables in Appendix (2.5) and (2.6) also provides additional descriptions of the data.

Outage loss: The amount of outage loss is separately computed for firms that invested in self-generation (L_s) and for those that didn't (L_f). This is computed from firm's annual sales volume and percentage of sales lost due to outages reported by the firm during the survey. Since all financial data including firm sales were reported in Local Currency Units (LCUs) in the WBES, the outage loss is converted to equivalent USD using the prevailing exchange rate for each country during the survey period.

Figure (2.1) shows that there is a considerable variation in outage time across countries ranging from less 2 in Namibia to more than 4 (in log days per year) in Nigeria. The corresponding percentage of sale lost due to outage ranges from 3% in Sudan and Namibia to about 12% in Ghana and Nigeria. The average outage time and the corresponding percentage of sales loss are positively correlated. This suggests that

[8]See Table 2.5

Figure 2.1: Outages Loss and Outage Time by Country



firms in a country where power outage is severe incur higher outage loss compared to firms in a country where the problem is moderate.

Outage time (lnH)

The variable outage time utilized in the study is computed from the reported frequency and duration of power interruptions that a firm faces in a month. Monthly outage time is obtained by multiplying frequency of power outages with its duration and then it is converted into yearly data assuming the same outage frequencies and duration throughout the year. The outage time–the number of days a firm face power cut from the public grid–also measures the reliability of power supply.

Power intensity dummy (PID)

The average industry-level power intensity is obtained from electricity expenditure as the percentage of firm's total cost. On the basis of the computed average industry-level power intensity, power intensity dummy (PID) is defined as a dummy variable

Table 2.1: Summary Statistics

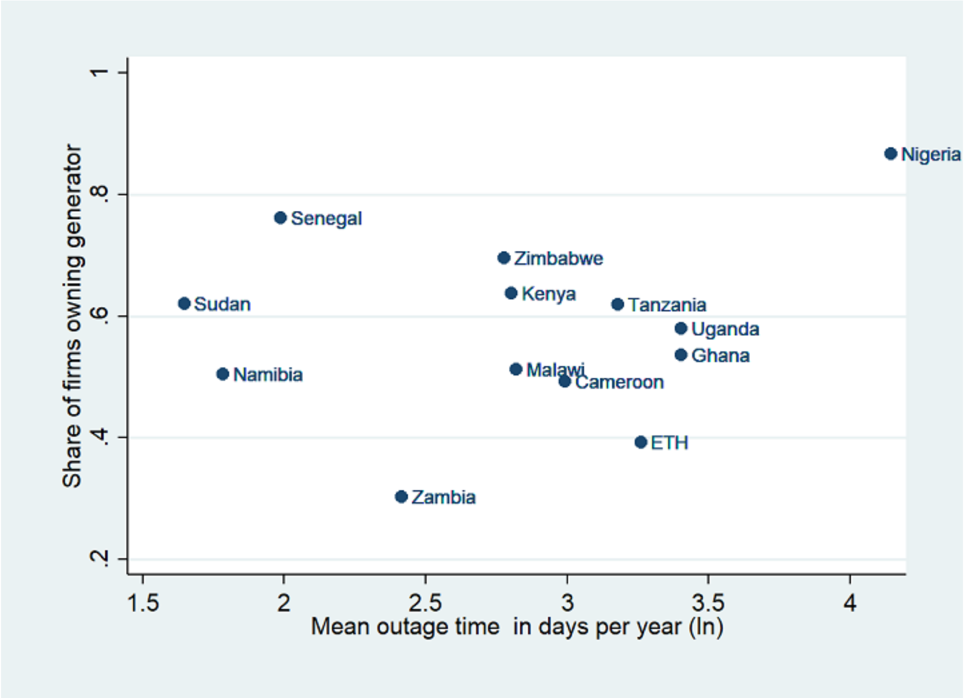
Variable	Description	Mean	Std.Dev.	Obs.
Outages(lnH)	Outage time in days/year	2.56	1.27	3029
Outage loss	Percentage of sales lost due to outage	8.65	8.53	2983
lnL_s	Outage loss (in \$/year) for adopters	13.03	4.24	1525
lnL_s	Outage loss (in \$/year) for non-adopters	11.71	5.23	1063
PID	Power intensity dummy	0.40	0.49	3029
$Constraint$	largest obstacle to firm's doing business	0.16	0.37	3209
lnE	Annual cost of electricity (\$/year)	7.16	3.35	2601
G	Percentage of firms owning generator	0.59	0.49	3029
G_{sh}	Share of electricity from self-generation	0.26	0.26	1730
lnL	Number of permanent full time workers	3.01	1.20	3029
Age of firm	Age of the firm (years)	2.51	0.70	2984
Experience (ln)	Experience of the top manager (years)	2.63	0.67	2949
Ownership	Percentage of firms owned by foreigners	0.20	0.40	3003
Exporters	Percentage of firms engaged in export	0.14	0.35	3029

Power intensity dummy (PID) is defined on the basis of average sector-level value of electricity expenditures as a percentage of total cost. PID takes a value of one if the average sector-level share of electricity from total annual cost is greater than median value. Obstacle to doing business is factors that firm reported as the main constraint to doing their business. These constraints are collapsed into two categories as electricity (1) and others factors (0) for easy interpretation. Observation counts differ due to non response and due to variable-specific cleaning procedures.

equal to one if the computed average industry level power intensity is greater than the median power intensity from whole observation in the data and zero otherwise.

Figure (2.2) plots the average share of firms owning generator against the mean outage time across countries. The Figure (2.2) illustrates that share of firms owning generator varies across countries. The cross-sectional correlation between outage time and share of firms owning generator is noisy but potentially positive suggesting that firms in a country where there is high power problem tends to invest in self-generation. For instance, in a country where electricity supply is highly unreliable like in Nigeria, about 86% of firms own generator. On the hand, in Senegal where power problem is relatively moderate, the share firms owning generator is about 76% which is greater than that of Ghana and Uganda where the power problem is more severe compared to Senegal. This shows there are factors other than the outage time that determines firm's decision to invest in self-generation. Firms facing the same

Figure 2.2: Outage Time and Share of Firms Owning Generator



Outage time is measured in days per year; its mean value is computed for each country. The correlation between outage time and share of firms owning a generator is noisy but potentially positive.

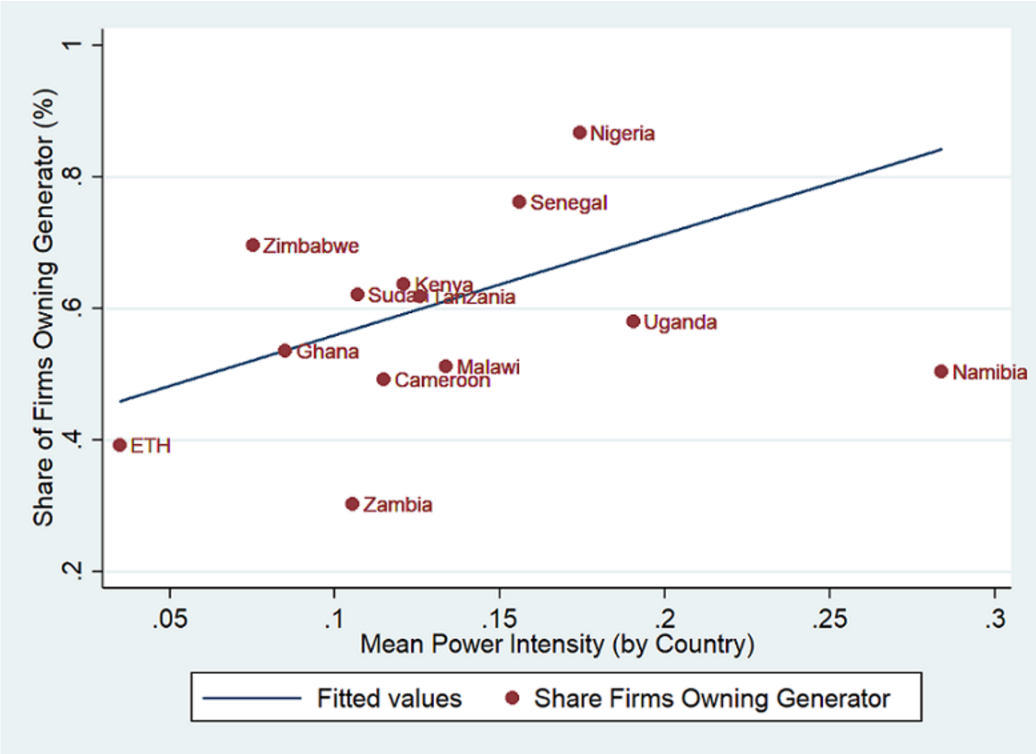
outage time my have different incentive to invest in self-generation, for example, due to their difference in the degree of their vulnerability to power outages. In this study, firm's vulnerability to power outage is captured by power intensity, which is computed by the ratio of firm's expenditure on electricity to total annual cost of production.

Figure (2.3) highlights important factor affecting firm's decision to invest in self-generation. There is a positive correlation between firm's power intensity and a decision to invest in self-generation. This suggest that two comparable firms facing the same duration of power outage may have different incentive to invest in generator due to differences in their degree of vulnerability to power outages[9].

In addition to the above graphical explanations, a simple regression of power related

[9]Firms degree of vulnerability to power outage mainly depends on the nature of business activities firms are engaged in. Outage of the same duration may cause large losses for some business activities while it creates only minor inconveniences for others Beenstock et al. (1997).

Figure 2.3: Self-generation and Firm's Power Intensity



Power intensity is computed by taking the ratio of firm's annual expenditure on electricity to total production cost. The Figure shows positive correlation between power intensity and incentive to invest in self-generation. Firms in a country with higher power intensity have higher incentive to invest in generator.

variables on outage time and power intensity is made. The variable "constraints" in Table (2.2) is an indicator variable which indicates whether a firm reported electricity as a main obstacle to doing its business or not.

Table(2.2) shows a meaningful correlation between self-generation and measures of electricity unreliability. The first column of Table (2.2) shows firms in a country where power supply is highly unreliable are more likely to invest in self-generation and the share of electricity coming from self-generation is higher for these firms. Column 3 indicates firms that report electricity as a main obstacle to doing their business more likely invests in self-generation, and for these firms the share of electricity from self-generation is higher compared to firms that didn't report electricity as a main obstacle to doing their business. Power intensity dummy is significant and positively correlated with both self-generation status and share of electricity

Table 2.2: Correlation of Outages with Power Variables

Dependent variable	$Outages(lnH)$ [1]	PID[2]	$Constraint$[3]
Self-generation (G)	0.0341***	0.121***	0.178***
	(0.006)	(0.018)	(0.023)
Share of self-generation (G_{sh})	7.883***	8.03***	12.32***
	(0.444)	(1.254)	(1.524)

The dependent variables are self-generation indicator which is binary outcome and takes value of one for firms owning generator, zero others, and share of electricity from self-generation (only for firms that adopted generator). For the purpose of estimating the correlation among the variables, linear probability model is assumed for self-generation indicator and the usual OLS is estimated for the later dependent variable. Figures in brackets are standard errors. *** significant at 1% level; ** significant at 5% level ; * significant at 10% level

from self-generation, suggesting that power intensive sectors are more likely to invest in self-generation and for these sectors, the share of electricity coming from self-generation is higher compared to less power intensive sectors.

The correlation matrix reported in Table (2.8) shows that power outage is positively correlated with both firm's decision to invest and the share of electricity coming from self-generation. Moreover, the Table shows positive and significant correlation between generator ownership and the variable "obstacle", which indicates positive and and significant correlation between electricity as a main obstacle to firm's doing business and the decision to invest in self-generation.

Other firm specific variables

Industry dummies and other firm characteristics capture important information about the cost of generator, and firm's financial barriers. The information on the cost of a generator is assumed to be captured by firms' characteristics, measured by firm size. Specifically, because electric generation exhibits economies of scale, larger firms are found to have smaller generation costs, and a higher probability of investing in self-generation (Steinbuks and Foster, 2010; Oseni and Pollitt, 2015). Firm size and age of firm capture firm's financial barrier. Large and old firms are in better position to ease access of external finance because of their established names and financial capacity and hence these firms have higher probability to invest in self-generation.

In addition, the study also utilizes other firm specific variables such as firm ownership–whether the owner of the business is domestic or foreigner, and export dummy–whether the firm is export oriented or not. Description of all variables, including firm specific variables are given in Table (2.1).

2.3.3 Model Specification

In this section, the empirical model is presented in line with the theoretical framework discussed in (2.2). The main implication of the theoretical model discussed in (2.2) is that under certain conditions, firms that expect positive NPV will invest in self-generation and there is a resulting outage loss differential between firms that invest in a self-generation and those that didn't. This is given as,

$$\begin{aligned} G_i = 1 \quad &\text{if} \quad NPV \geq 0 \\ G_i = 0 \quad &\text{if} \quad NPV < 0 \end{aligned} \tag{2.4}$$

where G_i represents firm's decision to invest in self-generation and it is 1 if the firm invests in self-generation and 0 otherwise.

As discussed in (2.2), firm's decision to invest in self-generation depends on outage time, the fixed and running cost of generator, and other firm characteristics. Depending on firm's decision in self-generation, there is a corresponding outage loss differential between firms that invested in self-generation and those that didn't. This can be captured by estimating the following switching regression,

$$Pr(G_i = 1) = \Phi(\beta_0 H_{ic} + Z_{ic}\gamma) \tag{2.5}$$

$$L_{sic} = \beta_{0s} H_{ic} + X_{sic}\beta_s + \varepsilon_{sic} \text{ if } G_i = 1 \equiv NPV \geq 0 \tag{2.6}$$

$$L_{fic} = \beta_{0f} H_{ic} + X_{fi}\beta_f + \varepsilon_{fic} \text{ if } G_i = 0 \equiv NPV < 0 \tag{2.7}$$

where equation (2.5) is a criterion (selection equation) that determines which regime occurs, Φ is the standard normal distribution function, i represent firm and c is country, H_{ic} is the outage time that firm i in country c faces, L_{sic} and L_{fic} are the outage loss to firms which invested in self-generation and those that didn't respectively, X_{sic}, X_{fic} and Z_{ic} are vectors of weakly exogenous variables in the respective equations given above; β_s, β_f and γ are vectors of parameters to be estimated, u_{ic} is error term in the selection equation (2.5). Assuming u_{ic}, ε_{sic} and ε_{fic} are normally distributed error terms with mean zero vector and the co-variance matrix is given by:

$$Cov(\epsilon_s,\ \epsilon_f,\ u_i) = \begin{bmatrix} \delta_s^2 & \delta_{sf} & \delta_{su} \\ \delta_{fs} & \delta_f^2 & \delta_{fu} \\ \delta_{us} & \delta_{uf} & \delta_u^2 \end{bmatrix} \tag{2.8}$$

where δ_u^2 is a variance of the error term in the selection equation, δ_s^2 and δ_f^2 are variances of the error terms in the continuous equations, δ_{su} is a co-variance of ϵ_s and u_i, δ_{fu} is a co-variance of ε_f and u_i.

The empirical specification of the model in (2.5)-(2.7) are given as:

$$\begin{aligned}
lnL_{sic} &= \beta_0 lnH_{ic} + \beta_{1s} lnE_{ic} + \beta_{2s} lnL_{ic} + \beta_{3s}' X_{ic} \\
&\quad + \lambda_{jc} + \eta_c + \varepsilon_{sic} \text{ if } G_i = 1 && (2.9) \\
lnL_{fic} &= \beta_{0f} lnH_{ic} + \beta_{1f} lnE_{ic} + \beta_{2f} lnL_{ic} + \beta_{3f}' X_{ic} \\
&\quad + \lambda_{jc+}\eta_c + \varepsilon_{fic} \text{ if } G_i = 0 && (2.10) \\
Pr(\quad G_i = 1) &= \Phi(\beta_0 lnH_{ic} + \beta_1 lnE_{ic} + \beta_2 lnL_{ic} + \beta_3' Z_{ic} + \lambda_{jc+}\eta_c) && (2.11)
\end{aligned}$$

where Z_{ic} = [ownership_i, exporter_ic , $lnAge_{ic}$, $lnExprience$, PID_{jc}], X_i=[ownership_ic, exporter_ic]; lnL_{sic} and lnL_{fic} are the amount of outage loss (in USD per year) that firms which invested in self-generation and those that didn't invest face respectively, lnH_{ic} is log of outage time that firm i in country c face in a year, PID_{jc} is the power intensity dummy for industry j, L_{ic} is the number of permanent full time workers, E_{ic} is the annul expenditure on electricity, λ_{jc} shows j industry dummies, η_c captures c country dummies and u_{ic} is a normally distributed error term with mean zero and variance of δ_u^2. Because of exclusion restriction imposed, managerial experience, age of firm and power intensity dummy (PID) appear only in the selection equation. The identification strategy and exclusion restriction imposed is discussed in detail in the next section.

2.3.4 Estimation Strategy

As discussed in (2.1), firm's decision to invest in self-generation depends on the outage time and firm characteristics. Firm's investment decision in turn affects the amount of outage loss that firms face. This makes the error terms in the outage loss equation and investment decision to be correlated. Estimation of such model by OLS and failing to account for the correlation between the error terms will result in a biased estimates. This motivates an endogenous switching regression model that accounts for any selectivity bias that may result from the correlation between the error terms in the outage loss equation and investment decision (Maddala, 1993; Fuglie and Bosch, 1995).

The endogenous switching regression model stated in (2.9)-(2.11) can be estimated by either two step least squares or maximum likelihood method. However, both of these estimation methods are inefficient and require potentially cumbersome adjustments to derive a consistent standard errors (Lokshin and Sajaia, 2004). The Full Information Maximum Likelihood (FIML) developed by Lokshin and Sajaia (2004), overcomes this problem and yields a consistent standard errors. Thus, this study employs the FIML to estimate the endogenous switching regression given in (2.9)-(2.11).

For the model described above to be identified, there should be at least one variable in the selection equation which is not included in the outage loss equations[10]. This variable should affect firms' decision to invest self-generation (the selection equation) but not directly affects the outage loss. To achieve this, managerial experience and average sector-level power intensity are included in the selection equation. The rationale of using managerial experience as an instrumental variable is based on the argument that the decision of whether a firm to invest in self-generation or not is mainly managerial decision which mainly depends on managerial experience to predict the nature of power interruptions and managerial capability to exploit firm's available resources. To the extent that good management is aimed at reducing firm's cost of production for a given level of output, managerial experience is expected to be negatively correlated with firm's decision to invest in self-generation.

The inclusion of power intensity in the selection is due to the fact that more power intensive sectors are willing to invest in a self-generation compared less power intensive sectors. The description of the data in Figure (2.3) and Table (2.2) supports

[10]This means there should be at least one variable in Z_i in equation (2.11) which is not included in $X_i^{'}s$ in equations (2.9) and (2.10)

this argument– firms that are more power intensive are more likely to own generator compared firms that are less power intensive. Taking a clue from this, to aid further the identification, a dummy variable indicating whether a firm is in a power intensive sector or not is computed, and interacted with outage variable. Power intensity dummy is created based on average sector-level electricity cost as a percentage of firm's total cost. A sector is then, classified as power intensive if the computed cost of electricity as a percentage of total cost is above the median (4.8%) and non-power intensive otherwise.

2.3.5 Conditional Expectations, Treatment and Heterogeneity Effects

The endogenous switching regression model in (2.9) and (2.10) can be used to compare the expected outage loss between firms that invested in self-generation and those that didn't. The expected outcomes with and without self-generation can be used to calculate the expected treatment effects [11] for each group. This can be addressed by estimating the counterfactual unmitigated outage loss level for each group. For example, the expected outage loss with self-generation for a sample group that actually invested in self-generation can be estimated from data on firms in this group. The expected outage loss without self-generation for this group is a counterfactual outcome. The same logic would describe the actual and counterfactual outcomes for a group of firms without self-generation. The conditional expected outage loss for both group of firms under actual and counterfactual conditions are presented in Table (2.3). Details on how the conditional expected values under actual and counterfactual conditions, treatment and heterogeneity effects are computed for each group is available in Annex (2.6.1).

[11] Investment in self-generation is considered as voluntary treatment in which firms choose (self-select) to invest in generator based on the anticipated gains.

Table 2.3: Definition of Expected and Treatment Effects

Investment Decision			
Sample	Invest	Don't invest	Treatment
Own generator	$E(L_s/X_s, G_i = 1)$	$E(L_f/X_f,\ G_i = 1)$	TT
No generator	$E(L_s/X_s, G_i = 0)$	$E(L_f/X_f,\ G_i = 0$	TU
Heterogeneity Effects	BH_1	BH_2	

L_s- is the outage loss that firms which invested in self-generation face, L_f- is the outage loss that firms which didn't invest in self-generation face, X_s- is the observed control variables and characteristics of firms that own generator, $X_f-$is the observed control variables and characteristics of firms that don't own generator, $G_i = 1$ if the firm invested in self-generation and 0 otherwise. $BH_1$is the base heterogeneity effect for firms that own generator with the counterfactual condition that firms that didn't invest in self-generation had invested in self-generation. BH_2 is the base heterogeneity effect for firms that didn't invest in self-generation with a counterfactual condition firms that didn't invest in self-generation had invested in self-generation. $TT-$measures the effect of generator adoption on firms that invested in generator; this is computed by taking the difference between the actual outage loss that these firms face and the outage loss under the counterfactual condition that if they had not invested in generator. $TU-$measures the effect of generator adoption on those firms that don't invested in a generator.

2.4 Results

2.4.1 Outage Loss and Investment in Self-generation

The coefficient estimates of outage loss equation with endogenous switching due to investment in self-generation are presented in Table(2.4). For a comparison, a single-equation outage loss with no switching was estimated with a generator ownership dummy (G) as explanatory variable. The coefficient estimates from this model are biased and inconsistent but are included here to compare with the switching regression model. The result obtained using pooled OLS is reported in the first column of Table (2.4) . The coefficient of generator ownership dummy (G) is positive and significant implying that firms that invested in self-generation face greater outage loss relative to firms without such investment. This result provides a preliminary answer to the hypothesis of the study discussed in (2.2). This may be a misleading conclusion, however, because additional endogenous effects on outage loss due to investment in self-generation have not been properly accounted for in this simple model.

The decision to invest in self-generation estimated by probit model for the switching equation is reported in the second column of Table (2.4). Industry and country dummies are included in the estimation. The results from this model can be interpreted as the influence of observable firm characteristics and other controls on firm's decision to invest in self-generation. The coefficient of outage time is positive and significant, indicating that outage time induce firms to invest in self-generation. The variable employment indicates the number of permanent full-time workers and the estimated coefficient of the variable is positive and significant. This suggests that a higher number of workers increases the likelihood that a firm invests in self-generation. More specifically, large firms have higher incentive to invest in self-generation compared to small firms during a period of power outages.

Table 2.4: Outage Loss by Backup-status

	Pooled OLS (1)		Investment decision (2)		Generator(3)		No generator (4)	
Variable	Coef.	Std.err	Coef.	Std.err	Coef.	Std.err	Coef.	Std.err
Outages(lnH)	0.049**	0.021	0.046**	0.026	0.367***	0.075	0.452***	0.112
Employment(ln)	0.436***	0.035	0.386***	0.033	0.824***	0.091	2.19***	0.151
Elec. expend.(ln)	0.515***	0.017	0.048***	0.015	0.230***	0.038	0.562***	0.070
Export	0.308***	0.089	0.012	0.092	0.482***	0.215	0.686*	0.417
Ownership	0.191***	0.089	0.190**	0.084	0.082	0.207	0.616*	0.381
Experience (ln)	0.009	0.052	-0.068*	0.037				
G	0.298***	0.072						
Age (ln)	0.086**	0.051	0.090**	0.035				
PID	-2.280	0.071	0.192***	0.046				
$Constant$	4.164***	0.476	-0.727**	0.235	6.79***	0.628	5.803***	0.845
ρ_1					-0.053	0.092		
ρ_2							0.951***	0.008
Industry dummies			Yes		Yes		Yes	
Country dummies			Yes		Yes		Yes	
Number obs.						2240		
Log likelihood						-6726		
Wald $\chi^2(17)$				1339			$Prob > \chi^2 = 0.000$	

LR test of independent equations: $\chi^2(1) = 827$ $Prob > \chi^2 = 0.000$

*** $P \leq 0.01$; ** $0.01 < P \leq 0.05$; * $0.05 < P \leq 0.1$. G is generator ownership , PID -is the power intensity dummy which is one for industries that have average power intensity above the median value (4.8%). and zero otherwise. Coefficients of $\rho_1$and ρ_2 measures the correlation between selection equation and the outage loss equations. The significance of ρ_1 shows the investment decision and the outage loss equation for those that didn't invest in self-generation are positively correlated. Furthermore, the likelihood ratio test rejects the null hypothesis of the two equations are independent in favor of the alternative hypothesis, justifying the estimation of endogenous model.

The coefficients of electricity expenditure and firm ownership are positive and significant. This suggest that large electricity consuming firms and foreign owned firms are more likely to invest in self- generation. The coefficient of power intensity dummy (PID) is positive and significant. This indicates that, due to the nature of their business activities, power intensive firms need a continues supply of power and the probability that these firms invest in self-generation is higher compared to less power intensive firms.

As reported in the second column of Table (2.4), the estimated coefficient of firm age is positive and significant which indicates that the likelihood that a firm invests in self-generation increases with age of the firm. This might possibly explains the vulnerability and financial capacity of old firms as compared to young firms. Old firms due to their established brand names, are more likely to have access to external finance for their operation, including investment in self-generation. On the other hand, old firms which run many establishments suffer a huge outage loss for the same outage time compared to young firms with a single or few establishments. This may make old firms to have higher incentive to invest in self-generation compared young firms.

The variable experience, which shows the managerial experience of top manager of the firm is negative and marginally significant. This shows, firms under the management of experienced manager have less incentive to invest in self-generation. This could be due to the fact that motivated and experienced managers take actions which minimizes the firm's production cost because investment in alternative source of electricity would add more to cost for a given level of output. Similar literature is that of Cissokho and Seck (2013) in which the authors explained a positive effect of power outage on firm's cost efficiency as a successful coping strategy. Experienced firms organize their activities in way that could cancel the expected adverse effects of power outages. According to Scott et al. (2014) this strategies could be in the form of shifting workers from tasks that are electricity intensive to tasks that are less electricity demanding, or that don't need electricity or intensify production at times when electricity is running and adapt to the realities of power availability. Thus, the result could explains the role of improved management practices in adapting to the electricity problem.

Next, the study turns to analyze the outage loss differential among firms that invested in self-generation and those that didn't, and examine the role self-generation in mitigating the outage loss. The FIML estimates of endogenous switching regression model for outage loss are reported in the third and fourth column of Table (2.4). The likelihood-ratio test, reported in the last rows of Table (2.4), is statistically significant indicating that there is a self-selection in adopting self-generation. The estimated correlation coefficient is positive and significant for firms that didn't invest in self-generation. This indicates the decision to invest in self-generation and the quantity of outage loss are correlated which shows an evidence of endogenous switching in the model.

As reported in Table (2.4), the determinants of outage loss are similar in sign and significance for both backup and non-backup[12] firms, but differ in magnitude. This observed differences in estimated coefficients could be due to the presence of heterogeneity in the sample or attributed to investment in self-generation. Identification of the heterogeneity effect in the sample and the role investment in self-generation for both group of firms are discussed in the following section.

The coefficient of outage time is positive for both group of firms. This shows outage loss increases with an increase in outage time. However, the impact is stronger on a group of firms that didn't invest in self-generation. For instance, a 1% increase in outage time increases annual outage loss for firms that invested in self-generation

[12]Backup firms are those firms that have invested in self-generation while non-bank up firms are those that don't.

by 0.37% while the same 1% increase in outage time increases the outage loss for firms without such investment by 0.45%. This shows about 23% more than the corresponding coefficient in the outage loss equation for firms with backup investment. This indicates firms that have invested in self generation have managed, even if partial, the effect of power outages.

Similarly, outage loss increases with firm size and expenditure on electricity for both group of firms, however, the impact is more pronounced on firms without self-generation. This also possibly explains the importance of investing in self-generation.

2.4.2 Analysis of Outage Loss Differential

The extent to which investment in self-generation has helped firms in mitigating outage loss can be answered by comparing the impact of self-generation on firms that have actually invested, the effect of treatment on treated (TT), and its impact on those that didn't invest under the condition that if they had invested in self-generation; the effect of treatment on untreated (UT). This is reported in Table (2.5). The result indicates firms that actually invested in self-generation would have incurred a greater outage loss if they had not invested in self generation. For instance, firms in Zambia would have incurred additional 36% more than their current outage loss if they had not invested in self-generation while the figure for firms in Ethiopia is about 99%. On the other hand, firms that didn't invest in self-generation would have reduced their current outage loss between 2% to 24% if they had engaged in self generation. This indicates the impact of self-generation is greater on firms that have actually invested in self-generation.

Table 2.5: Predicted Outage Loss and Treatment Effects

	Backup Firms			Non-Backup Firms		
Country	Actual (1)	Counter-factual (2)	TT (%) (3)	Actual (4)	Counter-factual (5)	UT(%) (6)
Cameroon	14.97	21.49	43.57	13.27	14.26	-7.43
Ethiopia	8.74	17.48	99.80	8.58	7.83	8.75
Ghana	10.94	16.76	53.10	8.26	10.03	-21.46
Kenya	15.33	22.66	47.84	13.30	14.20	-6.80
Malawi	15.58	21.36	37.04	13.30	15.09	-13.48
Namibia	11.38	16.71	46.75	8.97	11.10	-23.77
Nigeria	12.14	20.97	64.56	11.43	12.02	-5.17
Senegal	15.41	23.08	49.76	14.40	14.72	-2.23
Sudan	11.08	19.12	72.54	11.91	11.10	7.61
Tanzania	16.88	23.77	40.83	13.75	15.26	-11.04
Uganda	16.73	22.85	36.54	14.67	16.02	-9.20
Zambia	18.18	24.70	35.81	16.58	17.62	-6.27
Zimbabwe	10.72	17.19	60.28	9.00	10.27	-14.18

TT– is the effect of investment in self-generation on firms that invested and obtained by taking the difference between column 1 & column 2, then divided by the first column. UT–is the effect of investment in self-generation on firms that didn't actually invest, computed by taking the difference of column four and column five, then divided by column four. Both TT and UT are expressed in percentages and TT shows the outage loss that firms that have invested in self-generation would have incurred if they had not invested compared to the current unmitigated loss given in column 1. UT shows the amount of outage loss that firms didn't invest in self-generation would have reduced had they invested in self-generation. Positive UT figures for Ethiopia and Sudan shows firms that didn't invest in self-generation are better off by not investing in self-generation.

Considering the observed differences in the predicted outage loss between firms that invested in a self-generation and those that didn't, firms that invested in self-generation face higher outage loss on average in all countries except in Sudan compared to firms that didn't (See Table 2.5). This simple comparison is, however, misleading because it doesn't account for unobserved differences between the two groups that may affects outage loss. In order to account for this, the base heterogeneity for both group is computed as specified in equations (2.18)–(2.19) and the result is reported in Table (2.6). With the counterfactual condition that firms that didn't invest in self-generation had invested, BH1 as indicated in equation (2.18), the expected outage loss for firms that actually invested is higher than the outage loss under the counterfactual condition in each of the countries except in Nigeria and Sudan. Firms in Nigeria and Sudan faces almost the same outage loss under actual and counterfactual conditions indicating there is no systemic sources of variation between the two groups that could result in observable differences in outage loss. Similarly, with the counterfactual condition that firms that have invested in self-generation didn't invest, BH2 as indicated in equation (2.19), firms that have invested in self-generation still face higher outage loss than firms that didn't. This explains the degree to which these firms are vulnerable to power outages and their inability to completely back-up their electricity load.

Table 2.6: Predicted outage loss and heterogeneity effects

	Backup firms		Non-backup firms		Heterogeneity effects	
Country	Actual (1)	Counter-factual (2)	Actual (3)	Counter-factual (4)	BH1 (5)	BH2 (6)
Cameroon	14.97	21.49	13.27	14.26	0.71	8.21
Ethiopia	8.74	17.48	8.58	7.83	0.91	8.89
Ghana	10.94	16.76	8.26	10.03	0.91	8.50
Kenya	15.33	22.66	13.30	14.20	1.12	9.36
Malawi	15.58	21.36	13.30	15.09	0.48	8.05
Namibia	11.38	16.71	8.97	11.10	0.28	7.74
Nigeria	12.14	20.97	11.43	12.02	0.11	8.54
Senegal	15.41	23.08	14.40	14.72	0.68	8.68
Sudan	11.08	19.12	11.91	11.10	-0.08	7.21
Tanzania	16.88	23.77	13.75	15.26	1.61	10.02
Uganda	16.73	22.85	14.67	16.02	0.71	8.18
Zambia	18.18	24.70	16.58	17.62	0.56	8.11
Zimbabwe	10.72	17.19	9.00	10.27	0.45	8.19

BH1 is the base heterogeneity effect for backup firms with counterfactual condition that non-backup firms had invested in self-generation, and is computed by taking difference between the first column and 4th column. BH2 is the base heterogeneity for non-backup firms with the counterfactual condition that backup firms didn't invest in self-generation; and is computed by taking the difference between the second and third column.

2.4.3 Extensions and Robustness Checks

This section asses the sensitivity of the result to the identification assumptions. The identification in the previous section is based on the use of managerial experience and power intensity dummy in the investment decision equation and excluding them from the outage loss equation. To asses the validity of this assumption and examine sensitivity of the estimates to this assumptions, the model is re-estimated by relaxing some of the assumptions. Three alternative specifications are estimated and reported in Appendix (2.6.2). Compared to the baseline model reported in Table (2.4), the first alternative specification is estimated with managerial experience and interaction of power intensity dummy with outage time in the investment decision model. In the second alternative specification, in addition to the interaction of power intensity dummy with outage time, managerial experience is treated as categorical variable rather than continuous and industry dummies are excluded from the outage loss equation [13] . These categories are then included in selection equation. Finally, in the third alternative specification, industry dummies are excluded from both selection and outage loss equation compared to the baseline model.

Table (2.7) presents the correlation coefficients between errors terms in selection and outage loss equations under alternative specifications. The sign and significance of the correlation coefficients are maintained under all specifications.

Under the first alternative specification, the coefficient of interaction term, power intensity interacted with outage time, is positive and significant. This indicates power outages induce power intensive firms to invest more in self-generation compared to less power intensive firms. Other variables of the model have maintained their sign and statistical significance in both selection and outage loss equations. In all cases, alternative specifications does insignificant changes compared to the result from baseline specification (see Appendix 2.10–2.12).

[13]Managerial experience is categorized into five quintiles following (Iacovone et al., 2014). The first quintile 1 contains managers that have between 0 and 6 years experience, quintile 2 is from 7 to 11 years, quintile 3 is from 12 to 16 years, quintile 4 from 17 to 26 years and quintile 5 contains managers that have more than 27 years experience

Table 2.7: The Impact of Alternative Specifications on Correlation Coefficients

Specifications	ρ_1	Std. Err.	ρ_2	Std. Err.
Baseline specification	-0.053	(0.092)	0.951***	(0.008)
Alternative specification (1)	-0.065	(0.093)	0.950***	(0.008)
Alternative specification (2)	-0.059	(0.091)	0.950***	(0.007)
Alternative specification (3)	-0.052	(0.087)	0.948***	(0.008)

Figures in brackets are standard errors. In alternative specification (1), the interaction of PID with outages time is added to the investment decision equation compared baseline specification. Managerial experience is treated as categorical variable and industry dummies are excluded from outage loss equations in alternative specification (2); while in specification (3) only industry dummies are excluded from both the outage loss and selection equations compared to the baseline equation.

2.4.4 Why do Firms that Invested in Self-generation Face Higher Outage Losses?

As discussed in (2.4.2), firms that invested in self-generation would have suffered from 36% to 99% additional outage loss compared to the current outage loss the firms have incurred. This shows self-generation has helped these firms by reducing the outage loss by 36% to 99% that these firms would have incurred. However, comparing the outage loss between a group of firms that invested in self-generation and those that didn't, a group of firms that invested in self-generation continued to face higher outage loss compared to firms without such investment. Thus, a question that arises from the analysis is that why firms that invested in self-generation still suffers higher outage losses?

This is mainly due to the fact that firms make only partial investments which can't fully backup their electricity load. Table (2.7) shows that the share of electricity coming from self-generation is only 9% in Sudan, and it is 11% in Cameroon. Relatively high percentage of backup electricity is observed in Nigeria, which is about 53%. The implication is that firms may backup only critical components of their operation due to high cost of self-generation or lack of access to finance. The cost of self-generation is approximately 3 times as costly as the cost of electricity supplied by the public grid (Steinbuks and Foster, 2010; Adenikinju, 2003). Firms may also opt for less than full backup investment in self-generation due to financial constraint and choose to backup only critical components of their operation. Thus, a firm may invest in self-generation but remain vulnerable to power outages.

2.4.5 Future Research Agenda

This paper examined the role of investment in self-generation in mitigating outage loss and the outage loss differential between firms that invested in self-generation and those that didn't. The result shows that, despite their investment in self-generation, firms that invested in self-generation continuous to face higher outage loss compared to firms without such investment. This might be due to the inability of firms to self-generate the required power load by investing in self-generation. In this regard, Beenstock et al. (1997) also argued that investment in self-generation does not guarantee a complete mitigation of outage loss. For this matter, it is important to explore factors behind firm's sub-optimal investment in self-generation. For instance, factors such as firm's lack of access to finance could limit the scope of a firm's ability to invest in self-generation.

Table (2.8) shows classification of firms as credit constrained or not (see 2.6.3 for a definition firm's credit constraint) by firm size. Relatively high percentage of large firms are credit unconstrained while a large share of small firms were found to be credit constrained. This might shows that large firms are more likely to have access to external funds to finance their operations and hence less credit constrained than small firms.

In order to understand more about the correlation between lack of access to finance and firm's decision to invest in self-generation, a simple pairwise correlation between firm's investment decision in self-generation and alternative definitions of credit

Table 2.8: Classification of firms by alternative definition of credit constraint

Definition	**Constrained**	**Unconstrained**	**Total**
Perception approach	59%	41%	100%
Credit application information	47%	53%	100%
Firm Size	**Small**	**Medium**	**Large**
Percentage of Constrained	62.9%	56.9%	48.5%
Percentage of Unconstrained	37.1%	43.1%	51.0%

Perception approach is used to classify firms as credit constrained and unconstrained, for definitions of firm's credit constraint, see 2.6.3

Table 2.9: Correlation Matrix

Variables	G	G_{sh}	$Constraint$	$Constraint_1$	$Outage(ln)$
G	1				
G_{sh}	0.571***	1			
$Constraint$	-0.109***	-0.103***	1		
$Constraint_1$	-0.061***	-0.034**	0.338**	1	
$Outage(ln)$	0.216***	0.506***	0.106**	0.028	1

*** $P \leq 0.01$; ** $0.01 < P \leq 0.05$; * $0.05 < P \leq 0.1$. G is firm's decision to investment in self-generation which takes 1 for firms that invested in self-generation and zero other wise. G_{sh} is the share of electricity from self-generation, $Constraint$- is the perception approach to credit constraint definition and takes value from 0 to 4 with higher value implies more credit constraint. $Constraint_1$ is the credit application information definition of credit constraint and takes 1 if the firm is credit constrained and 0 otherwise. Outages is the total power interruption in days a firm faces in a year.

constraint is given in Table (2.9). The correlation matrix shows a meaningful result in which all measures of credit constraints are negatively correlated with both firm's decision to invest and the share of electricity from self-generation. This suggests that credit constraints affect a firm's decision to invest and the share of electricity from self-generation negatively. On the other hand, power outage is positively correlated with both firm's decision to invest and volume of investment which implies unreliable supply of public electricity force firms to invest in private substitutes. Moreover, Table (2.9) shows that positive and significant correlation between the different definitions of credit constraints which implies the consistency of the alternative measures of credit constraints. Thus, this preliminary result supports the augment given in section 2.4.4 above that firms choose to make sub-optimal investment in self-generation due to lack of access to finance.

2.5 Conclusion and Policy Implications

2.5.1 Conclusions

The study examined the role of self-generation in mitigating the outage loss and evaluated the outage loss differential between firms that invested in self-generation and those that didn't. To address this, the study used the WBES data collected from firms operating in 13 SSA countries. The study employed an endogenous switching regression in a counterfactual framework to explain the outage loss differential among firms that invested in self-generation and those that didn't. The result shows that the decision to invest in self-generation is affected by firm characteristics such as firm size, export engagement, and business environment. Moreover, the study shows that firms operating in power intensive sectors are more likely to invest in self-generation compared to firms in less-power intensive sectors.

Outage loss is separately estimated for firms that invested in self-generation and those that didn't. The result shows a differential impact of outage intensity and firm size on outage loss with stronger effect observed on firms that didn't invest in self-generation. Even though this differences could be attributed partially to the heterogeneity effect among the two group, it explains the role of self-generation in mitigating outage losses.

Although self-generation has reduced the amount of outage loss for firms that have invested in self-generation, these firms continue to face higher unmitigated outage loss relative to firms that didn't invest in self-generation. Comparing outage loss between the two group under actual and counterfactual conditions, higher unmitigated outage loss is observed among firms that invested in self-generation. This indicates the degree to which these firms are vulnerable to power outages and their inability to completely backup their electricity demand relative to the required electricity load. In spite of this, firms that have invested in self-generation would have incurred

36%-99% more outage loss if they didn't engage in self-generation. Similarly, firms that didn't invest in self-generation would have reduced their outage loss by 2% - 24% if they had engaged in self generation.

Thus, it can be concluded that firm's willingness to invest in self-generation primarily depend not only on outage time but also the degree to which firm's operation is vulnerable to power outages and the effect of self-generation is higher on a group of firms that have invested in self-generation.

2.5.2 Policy Implications

From the above conclusions, the following policy implications can be drawn. The first policy implication of the study is differential supply interruption should be followed by public authorities based on firms' degree of vulnerability. It would be beneficial if firms whose operation are more vulnerable to power outages are allowed to get preferential power supply advantage. This could be possible by arranging a binding contract between vulnerable firms and power companies, so that power companies charge the optimal tariff for supplying secure power for vulnerable firms. In turn, firms should be compensated if the power companies fail to do so. This helps vulnerable firms expand their production without fearing the risk of power outages.

The result indicates in countries where the supply of electricity highly unreliable like in Nigeria, the expansion of self-generated electricity is high (about 86% of firms own generator)–generally a more expensive electricity source than the public grid. This indicates a high willingness to pay for reliable power. This may provide an opportunity for the government and the power companies to finance investments that make the power supply more reliable. Thus, public authorities should remove subsidies and introduce optimal tariffs that are cost recovering for new grid investment.

2.6 Appendix

Table 2.5: Sample Size by Country

Country	Sample size	Percentage	Survey Year
Cameroon	126	4.16	2016
Ethiopia	423	13.97	2015
Ghana	280	9.24	2013
Kenya	317	10.47	2013
Malawi	170	5.61	2014
Namibia	117	3.86	2014
Nigeria	505	16.67	2014
Senegal	126	4.16	2014
Sudan	227	7.49	2014
Tanzania	194	6.40	2013
Uganda	119	3.93	2013
Zambia	241	7.96	2013
Zimbabwe	184	6.07	2016
Total	3,029	100	

Source: Author's computation based on data described in the text.

Table 2.6: Table 9: Sample size by sector and firm size

Sector	Firm size			Total
	Small	Medium	Large	
Manufacturing	699	475	255	1429
Services	726	360	139	1225
Retails	269	83	23	375
Total	1694	918	417	3029

2.6.1 Conditional Expectations, Treatment and Heterogeneity Effects

The conditional expected outage loss for both group under actual and counterfactual conditions are presented in Table (2.8). These conditional expectations are defined

Table 2.7: Percentage of electricity coming from self-generation

Share of electricity from self-generation		
Country	Mean G_{sh} (%)	Sdt.Dev.
Cameroon	11.12	9.62
Ethiopia	21.94	24.78
Ghana	18.04	12.56
Kenya	13.30	13.54
Malawi	20.02	19.61
Namibia	21.09	20.53
Nigeria	53.79	27.40
Senegal	12.71	17.13
Sudan	9.31	14.27
Tanzania	22.45	13.11
Uganda	14.76	18.96
Zimbabwe	19.96	22.70

Share of electricity coming from self-generation is computed as the ration of electricity from self-generation to total electricity load of the firm.

as follows:

$$E(L_s/X_s\ ,\ G_i = 1) = X_s\beta_s + \delta_s\rho_1\frac{f(\gamma Z_i)}{F(\gamma Z_i)} \tag{2.12}$$

$$E(L_f/X_f\ ,\ G_i = 0) = X_f\beta_f + \delta_f\rho_2\frac{f(\gamma Z_i)}{F(\gamma Z_i)} \tag{2.13}$$

$$E(L_s/X_f\ , G_i = 0) = X_f\beta_s - \delta_f\rho_2\frac{f(\gamma Z_i)}{(1 - F(\gamma Z_i))} \tag{2.14}$$

$$E(L_f/X_s\ ,\ G_i = 1) = X_s\beta_f - \delta_s\rho_1\frac{f(\gamma Z_i)}{(1 - F(\gamma Z_i))} \tag{2.15}$$

where F is a cumulative normal distribution function, f is a normal density distribution, ρ_1 measures correlation between ε_s and u_i, ρ_2 measures correlation ε_f and u_i.

Equations in (2.12) and (2.13) are important to estimate the expected unmitigated outage losses for firms that invested in self-generation and those that didn't for firms actually observed in the sample respectively, while Equations (2.14) and (2.15) are their respective counterfactual expected unmitigated outage losses. The use of these

Table 2.8: Correlation Matrix

Variables	G_{ow}	G_{sh}	*lnoutages*	*PID*	*Obstacle*
G_{ow}	1				
G_{sh}	0.443***	1			
lnoutages	0.205***	0.392***	1		
PID	0.156**	0.152***	-0.004	1	
obstacle	0.168***	0.190**	0.146**	-0.064**	1

The correlation matrix shows a positive correlation between outage time and both firm's decision to invest and volume of investment which implies unreliable power supply induce firms to invest in private substitutes. Moreover, the Table shows positive and significant correlation between generator ownership and the variable "obstacle", which indicates positive and and significant correlation between electricity as a main obstacle to firm's doing business and the decision to invest in self-generation

Table 2.9: Definitions of conditional expectations, treatment and heterogeneity effects

	Investment decision		
Sample	Invest	Don't invest	Treatment
Own generator	$E(L_s/X_s, G_i = 1)$	$E(L_f/X_f,\ G_i = 1)$	TT
No generator	$E(L_s/X_s, G_i = 0)$	$E(L_f/X_f,\ G_i = 0$	TU
Heterogeneity Effects	BH_1	BH_2	

L_s- is the outage loss firms that invested in self-generation face, L_f- is the outage loss firms that didn't invest in self-generation face, X_s- is the observed control variables and characteristics of firms that own generator, X_f–is the observed control variables and characteristics of firms that don't own generator, $G_i = 1$ if the firm invested in self-generation and 0 otherwise. $BH_1$is the base heterogeneity effect for firms that own generator with the counterfactual that firms that didn't invest in self-generation had invested in self-generation. BH_2 is the base heterogeneity effect for firms that didn't invest in self-generation with a counterfactual condition firms that didn't invest in self-generation had invested in self-generation. TT–measures the effect of generator adoption on firms that invested in generator; this is computed by taking the difference between the actual outage loss that these firms face and the outage loss under the counterfactual condition that if they had not invested in generator. TU–measures the effect of generator adoption on those firms that didn't invest in a generator .These concepts are discussed below.

conditional expectations, combined with consideration of the self-generation variable as a treatment variable, allows the estimation of the causal effects of self-generation on outage loss.

Following Heckman et al. (2001), the effect of generator adoption on firms that have actually adopted, "the effect of treatment on treated (TT)," is computed by taking the difference between equation (2.12) and equation (2.15):

$$TT \;=\; E(L_s/X_s,\ G_{owi} = 1) - E(L_f/X_f,\ G_{owi} = 1) \tag{2.16}$$

This represents the effect of investing in self generation on firms' outage loss that have actually invested in self-generation. Similarly, the effect of self-generation on firms that didn't invest in self-generation, "the effect of treatment on the untreated

(TU)" is computed by taking the difference between (2.13) and (2.14).

$$TU \quad = \quad E(L_f/X_f,\ G_{owi}=0) - E(L_s/X_s,\ G_{owi}=0) \tag{2.17}$$

The conditional expectation in equations (2.12)-(2.15) can also be used to compute the heterogeneity effects. For instance, firms that invested in self-generation may have faced higher outage loss than those firms that didn't invest regardless of their decision to invest in self-generation but because of the nature their business and other firm characteristics. Adapting Carter and Milon (2005) concept of base heterogeneity, the effect of base heterogeneity for the group of firms that invested in self-generation is computed by taking the difference between equation in (2.12) and (2.14)

$$BH_1 = E(L_s/X_s,\ G_i=1) - E(L_s/X_s,\ G=0) \tag{2.18}$$

Similarly, for those firms that didn't invest in self-generation, the effect of base heterogeneity is the difference between equation (2.13) and (2.15)

$$BH_2 \quad = \quad E(L_f/X_f, G_i=0) - E(L_f/X_f, G_i=1) \tag{2.19}$$

2.6.2 Alternative Specifications for Switching Regression

Table 2.10: Alternativee Specification 1

	Adoption decision		Adopters		Non-adopters	
Variable	Coef.	Std.err	Coef.	Std.err	Coef.	Std.err
Outages(ln)	0.0203	0.027	0.366***	0.075	0.446***	0.112
Employment(ln)	0.386***	0.033	0.818***	0.091	2.17***	0.151
Elec. expend.(ln)	0.047***	0.015	0.229***	0.038	0.569***	0.070
Export	0.009	0.092	0.482**	0.215	0.684*	0.417
Ownership	0.189**	0.084	0.079	0.207	0.618*	0.381
Experience (ln)	-0.068*	0.037				
$A_f(ln)$	0.087***	0.035				
PID*Outages(ln)	0.064***	0.016				
$Constant$	-0.631**	0.232	6.82***	0.629	5.64***	0.930
ρ_1			-0.065	0.093		
ρ_2					0.950***	0.008
Industry dummies	Yes		Yes		Yes	
Country dummies	Yes		Yes		Yes	
Number Obs.			2237			
Log likelihood			-6796			
Wald $\chi^2(17)$	1335				$Prob > \chi^2 = 0.000$	
LR test of independent equations: $\chi^2(1) = 831$ $Prob > \chi^2 = 0.000$						

PID–is the power intensity dummy, which takes value of one if the average industry -level power intensity is greater than the median value and zero other wise. In this specification, in addition to managerial experience, identification is achieved by the inclusion of the interaction term $PIDlnoutages$ which is the interaction of power intensity indicator and the outage time.

Table 2.11: Alternative Specification 2

	Adoption decision		Adopters		Non-adopters	
Variable	Coef.	Std.err	Coef.	Std.err	Coef.	Std.err
Outages(ln)	0.025	0.027	0.360***	0.074	0.459***	0.110
Employment(ln)	0.387***	0.032	0.834***	0.090	2.18***	0.148
Elec. expend.(ln)	0.050***	0.015	0.226***	0.037	0.550***	0.068
Export	0.004	0.090	0.493**	0.212	0.811**	0.417
Ownership	0.178**	0.205	0.079	0.207	0.487*	0.371
$Expc2$	-0.157***	0.066				
$Expc3$	-0.151**	0.069				
$Expc4$	-0.166***	0.068				
$Expc5$	-0.178**	0.078				
Age(ln)	0.071**	0.034				
PIDOutagesln	0.058***	0.015				
$Constant$	-0.538**	0.202	6.27***	0.529	5.98***	0.818
ρ_1			-0.059	0.091		
ρ_2					0.950***	0.007
Industry dummies	Yes		No		No	
Country dummies	Yes		Yes		Yes	
Number Obs.			2291			
Log likelihood			-6867			
Wald $\chi^2(17)$		1356			$Prob > \chi^2 = 0.000$	
LR test of independent equations: $\chi^2(1) = 612$ $Prob > \chi^2 = 0.000$						

PID–is the power intensity dummy, which takes value of one if the average industry level power intensity is greater than the median value and zero other wise. In this specification; industry dummies are excluded from outage loss equations.

Table 2.12: Alternative Specification 3

	Adoption decision		Adopters		Non-adopters	
Variable	Coef.	Std.err	Coef.	Std.err	Coef.	Std.err
Outages(ln)	0.057**	0.025	0.312***	0.073	0.522***	0.113
Employment (ln)	0.430***	0.027	1.066***	0.083	2.905***	0.133
Export	0.052	0.086	0.373*	0.215	0.712*	0.422
Ownership	0.112	0.084	0.252	0.200	0.691*	0.376
Experience (ln)	-0.049	0.035				
Age(ln)	0.064**	0.031				
PID	0.205***	0.042				
$Constant$	-0.257	0.163	8.032***	0.416	9.986***	0.676
ρ_1			-0.052	0.087		
ρ_2					0.948***	0.008
Industry dummies	No		No		No	
Country dummies	Yes		Yes		Yes	
Number Obs.			2466			
Log likelihood			-7512			
Wald $\chi^2(16)$		1394			$Prob > \chi^2 = 0.000$	
LR test of independent equations: $\chi^2(1) = 1154$ $Prob > \chi^2 = 0.000$						

Compared to the third specification, industry dummies are excluded from both adoption decision equation and the outage loss equations. Identification is achieved through the inclusion of PID and Experience in decision equation.

2.6.3 Definition of Credit Constraint

In the literature, there are different approach to define firm's credit constraint. Two of them are discussed here.

Perception approach: In the perception approach to credit constraint, firms are asked to rate the degree to which lack of access to finance is an obstacle to doing their business Beck and Demirguc-Kunt (2006); Asiedu et al. (2013). In the WBES, firms are given a categorized choice from no obstacle to very severe obstacle. Following Hansen and Rand (2014); Asiedu et al. (2013) approach, firms were categorized as credit constrained if they has reported lack of access to finance is moderate, major and very severe constraint to doing its business and zero otherwise (details are reported in Table 2.13.

Credit application information: based on the credit application information, firms are classified as credit constrained or not based on whether firms have applied for a loan and stated reasons for not applying. Following earlier studies in the area, Hansen and Rand (2014); Bigsten et al. (2003), a firm is categorized as credit constrained–$constraint_1$– if: (i) the firm has applied for a loan and was denied, (ii) didn't applied for a loan due to reasons such as "application procedures were complex", "collateral requirements were too high", or "possible loan size and maturity were insufficient". If firms did not apply for a loan because they don't need one or applied for a loan and were approved, they are classified as unconstrained (see Table 2.14 for details).

Table 2.13: Access to finance as obstacle to doing business

To what degree access to finance is obstacle to the current operation of this firm?	Percentage	Category
No obstacle	17.37%	unconstrained
Minor Obstacle	23.28%	unconstrained
Moderate obstacle	22.13%	constrained
Major obstacle	23.87%	constrained
Very severe obstacle	13.36%	constrained

The column category shows whether the firm is credit constrained or not which is based on the perception approach to definition of credit constraint in section 2.2

Table 2.14: Loan application and reasons for not applying

		Did this establishment	applied for credits or loan?			
Yes		19.83%				
		Outcome of	application			
	approved		rejected		in process	
	94.22%		0.92%		4.85%	
Category	unconstrained		constrained		NC	
No		80.17%				
		reason for not applying				
	no need	complex pro.	interest unfav.	coll. requ.	loan size	others
	46.39%	10.78%	17.66%	12.75%	2.04%	10.38%
Category	unconst	constr	constr	constr	constr	constr

Categories are based on the definition given above, the credit application information approach. Unconst and constr indicates unconstrained and constrained respectively. Firms that have applied but their application is still in process during the survey are not considered (NC).

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