LIGHTS OFF, LIGHTS ON:
THE EFFECTS OF ELECTRICITY SHORTAGES ON SMALL FIRMS

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Abstract

The Ghanaian Dumsor energy crisis of 2014/2015 led to dramatic, frequent, and largely unpredictable outages around the country. This paper exploits variation across garment making firms in self-reported blackout days using daily data over 7 weeks, combined with weekly panel data on firm inputs, outcomes, and network activity to study the effects of electricity shortages on small firms. We supplement our main identification with data on government load shedding schedules, and gps data on all electricity transformers in our sample area. Blackouts lead to economically meaningful declines in both weekly revenues and weekly profits; each additional blackout day is associated with an 11% decrease in weekly profits on average. Firm owners respond to blackouts by working fewer hours during blackouts, without fully shifting labor supply onto non-blackout days. Expenditures on wages fall, suggesting that firm owners may shift from the use of higher paid workers to low wage apprentices.

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1 Introduction

Infrastructure availability, quality, and reliability are potentially important determinants of private sector development. In Ghana, as in many low-income countries, electricity demand often outstrips supply, and power is erratic and frequently unavailable. Despite both public and private efforts to develop new capacity, major power crises plagued Ghana in 2006-07, and 2012-present. The 2006-07 crisis is estimated to have cost the country 1% in lost GDP growth (World Bank, 2013). Understanding the impact of lacking infrastructure and the ways in which firms and workers adjust their behavior to optimize given unreliable infrastructure are thus important areas for research. Relatively little work has been done to understand how electricity shortages affect the private sector, with particularly little evidence on these effects for small and informal firms, the dominant form of employment in many developing countries.

This paper makes use of daily micro data on electricity outages and labor hours, and weekly data on revenues and profits in a panel of firms in Ghana to estimate the effects of blackouts on firm output and input choices. We study a period of heavy load shedding and frequent, unpredictable blackouts in March and April of 2015. Throughout the paper we will colloquially refer to the period as the "lights crisis", though we are estimating the effects of electricity outages, not simply loss of access to artificial light. The sample consists of all garment-making firms with any access to electricity in a mid-size district capital in Volta Region, and includes detailed weekly network activity data derived in part from a full map of connections between sample firm owners. The micro scale of the data and the additional network feature allow us to explore two supplementary questions: how do firms adjust behavior to ameliorate the negative output effects of blackouts? And, which firms are worst affected by blackouts?

Our primary identification strategy relies on the assumption that firm-level blackouts, conditional on time fixed effects which control for the overall probability of a blackout, are as good as random. These main specifications take self-reported daily blackout measures from 343 firms over 49 days as noisy but reliable measures of true cross-firm blackouts. We check this identification assumption by confirming that the self reported daily blackout measures, conditional on date fixed effects, are not related to baseline firm characteristics. Though not all point estimates are a precise zero, only three of fifteen are statistically significant and none are economically significant.

Using these main specifications with self-reported blackout data, we perform analysis at the daily, weekly, and study-wide level. At the weekly level, we first confirm that blackouts have a negative impact on firm output and profitability. Using self-reported revenues, detailed self-reported counting of individual completed orders, and profits measured as total revenues less total expenses in a survey week, each additional blackout day is associated with 5.43 GhC fewer revenues and .42 fewer orders per week. With expenses falling only 1.67 GhC per blackout day, this results in 3.75 GhC less profits per week per blackout day. With average weekly profits at 34.55 and outages reported for 31% of days, these effects are economically significant. Note that this identification strategy uses cross-firm blackout variation, and thus underestimates the total effect of the lights crisis. Dates on which the entire town had a blackout will not contribute to blackout variation with the inclusion of time fixed effects.

We next document that although point estimates on expenses are negative in all categories, wage expenses on wages are large and significant. This finding is evidence that the lights crisis affected not only firm owners, but paid wage workers as well. In our context, the firm does not fully insure the worker against productivity fluctuations. At the study-wide level, we see evidence of generator purchases, but only at a very minuscule scale. We find no evidence of other equipment substitutions over the period in response to the lights crisis.

At the daily level, we see very strong evidence that owner labor falls in response to blackouts. Firm owners worked approximately half an hour less on average on blackout days and are 4% less likely to work at all. In essence, we see evidence that firm owners are shifting their own labor onto more productive non-blackout days. We explore this labor supply response more fully by disaggregating by day of the week, and uncover a reasonable pattern. Firm owners' intensive margin in responsive on all days but Sunday, while the extensive margin is particularly responsive on Saturday.

One major contribution of this study is to explore the ways in which small firms are able to ameliorate the negative effects of blackouts (as compared, say, to larger firms). Using inter-temporal responses, we see that firm owners work more on days with lights that follow a blackout day, but that the 0.18 additional hours worked does not fully compensate for the half an hour average work lost on the previous blackout day. Firms like these, where firm owner labor supply is the primary input, are ubiquitous in Africa and around the developing world. To the extent that firm owner labor supply is more difficult to more inter temporally, we should expect these types of firms to suffer more from productivity variation induced by blackouts. We also confirm that profits per owner hour and wages per worker hour are negatively affected by blackout, as confirmation of the productivity variation induced by blackouts.

In a series of robustness checks, we explore how our point estimates change in response to alternative measures of blackouts. First, we include firm fixed effects in daily specifications, controlling for any time fixed firm specific endogeneity. The point estimates on firm owner intensive and extensive labor supply are remarkably stable. Next, we restrict the sample to days preceding weekly survey. That is, we use only responses for yesterday in daily specifications, in an effort to ameliorate recall error over the week. Again, our point estimates on firm owner intensive and extensive labor supply are negative.

Using data on official government load shedding schedules (which contain only cross-time variation), we compare firms with electricity access to others in our sample without electricity access on blackout and non-blackout days. Blackouts appear only to affect the labor supply of firm owners in firms with electricity connections, and the point estimate on reduction in hours worked is again remarkably stable.

Finally, we collect data on all electricity transformers in the town we study. Using GPS data on both transformers and firms, we match firms to the closest of the 24 transformers in the data, and recode the blackout data by aggregating across blackout self-reports in each transformer by date cell. The rationale behind this robustness check is that blackouts can be driven not only at the (much larger) substation level, but also at the transformer level within a town. Using this new (potentially noisier, but more grounded in clustered blackout generation) transformer-level blackout data, we show that our main results on weekly level revenues and profits, and daily level labor supply hold.

Lastly, we explore heterogenous effects of blackouts on firms. The effects of a blackout are heterogeneously strong for firms with more electricity intensive equipment and firms with higher paid "paid workers" at baseline. They are less strong for firm owners with at least one lower paid apprentice at baseline, suggestive of adjustment tactics that involve using apprentices and non-electric equipment to respond to blackouts. We also observe spillover effects between firms that are network connected at baseline. Blackout days on which at least one baseline network member does not have a blackout spur a lower labor response and are less costly to firms, an interesting example of co-insurance within a local industry network.

This paper contributes to the relatively sparse literature considering the firm-level consequences of electricity shortages. Allcott, Collard-Wexler and O'Connell (2014) is perhaps the most closely related to this paper, estimating yearly impacts of shortages on the universe of formal manufacturing firms in India. Another closely related paper is Fisher-Vanden, Mansur and Wang (2015), studying the impact of outages on large manufacturing firms in China. Our paper differs in that we focus on a sample of small firms and high frequency micro data, directly measuring short-run losses and coping strategies, which themselves may differ between large and small firms.

The estimated effect of blackouts on small firm contributes to the literature on constraints to the growth and profitability of small firms. For example, De Mel, McKenzie and Woodruff (2008) considers access to capital, finding high rates of return to capital in microenterprises in Sri Lanka; Bruhn, Karlan and Schoar (2013) show an impact of randomly offered consulting services on the productivity of small firms in Mexico; and Hardy and McCasland (2015) present experimental evidence from Ghana that small firms are labor constrained.

This paper also contributes to a somewhat unresolved literature in labor economics on labor supply elasticity between more and less productive work time. Camerer et al. (1997) and Farber (2014) present evidence on the labor supply of taxi drivers; Chang and Gross (2014) considers the labor supply of pear packers; Nguyen and Leung (2013) examines labor supply in fisheries; and Oettinger (1999) studies the labor supply of stadium vendors.

The paper proceeds as follows: In Section 2, we describe the context of our study, providing background on Ghana's electricity crisis and the garment sector. In Section 3, we describe our study and our data. In Section 4, we discuss our main estimation strategies and the source of blackout variation across firms. Section 5 presents the main results. In Section 6, we go through a series of robustness checks. Section 7 explores heterogeneous effects. Section 8 concludes.

2 Context

2.1 Electricity in Ghana

Electricity generation in Ghana is dominated by hydropower. The Akosombo Dam, which supplies the majority of Ghanaian power, was completed in 1965 with an installed capacity of 912 megawatts. It was later upgraded to a capacity of 1,020 megawatts, but due to technical inefficiencies, only about 900 megawatts of reliable capacity remain. In the 1980's, hydropower generation in Ghana was augmented to include the downstream Kpong Dam, with installed capacity of about 150 megawatts. The Volta River Authority (VRA), the public utility responsible for the power supply and created to run Akosombo by an act of parliament in 1961, expanded electricity generation capacity to thermal power starting in the 1990's. The Tema and Takoradi thermal power plants have a combined capacity of almost 500 megawatts. In addition, a third major hyrdopower plant was completed in 2013 with installed capacity of 120 megawatts [1].

Despite efforts to bolster public investment in the electricity sector, major shortages remain common. Weather variation and drought are often linked both anecdotally and empirically to reduced production in the hydropower sector, which may be exacerbated by climate change and more erratic rainfall patterns in recent years (Bekoe and Logah, 2013). Another major contributor to shortages is that industrial and residential demand has grown at about 10-15% per year over the last 15-20 years, as Ghana's economy has grown (Mathrani, 2013)[2]. In addition, a large share of total output is reserved for the Volta Aluminum Company (VALCO) and the mining industry. Other potential contributors to shortages include inefficient public administration of the existing infrastructure at the VRA, and mandated subsidies at the Electricity Commission of Ghana (ECG), the distribution arm of government administration, which make it difficult to finance new public investment. Efforts to encourage private investment have grown as outages have become more and more severe, but demand is still widely believed to exceed supply.

We discuss micro-level electricity technicalities in the identification section below.

[1] Additional public investment came in the form of the West Africa Gas Pipeline, the first of its kind in Africa, which was intended to transport relatively affordable natural gas from Nigeria to Benin, Togo, and Ghana, and was completed in 2009. The pipeline was damaged by pirates trying to board an oil taker off the cost of Togo in 2012. Interruption in the supply of natural gas continued through the period studied in this paper, and Ghanaian thermal plants were forced to use more expensive crude oil, causing more problems for the power generation sector.

[2] Another contributor to demand growth was a wide-scale rural electrification program in the 1990's that expanded the grid to more parts of Ghana.(Abeberese, 2016)

2.2 The Dumsor Crisis

Dumsor, or Dum So, derives from the words for on and off in the Asante Twi, Akuapim Twi, and Fante languages. The term was first used during the electricity rationing program associated with a severe drought in 1997, and gained prominence again after the West Africa Gas Pipeline damage in 2012. Protests in 2014 and 2015 were widespread as outages became longer and more erratic around the country. Official ECG load shedding schedules moved from 12 hours on/6 hours off, to 12 hours on/12 hours off, to 12 hours on/24 hours off over the course of many months. In addition, the schedules became less and less reliable as the crisis wore on into late 2014 and into the hot harmattan season of early 2015. Our data comes from March and April 2015, just at the tail end of the harmattan season.

The World Bank Enterprise Surveys in Ghana happen to have been collected during two periods of extreme power crisis, in 2007, during the 2006-07 power crisis and in 2013, at the beginning of the 2012-present Dumsor crisis. As such, their estimates of the firm-level burden of lacking electricity may reflect that particular timing. In the 2013 survey, 61% of firms cite electricity as a major constraint to firm performance, as compared to 43% citing corruption and 62% citing access to finance. This figure is fairly constant across the three major firm size strata (61% for firms of size 5-19 workers, 61% for firms of size 20-99, and 63% for firms of size 100+). Firms in the sample estimated losses due to electricity outages to be 11.5% of annual revenues.

2.3 Garment Making

Bespoke garment making firms are ubiquitous in many parts of Africa and the developing world. Nearly all garments produced by these small firms are made-to-order, for special occasions like funerals and weddings, as dress attire for church, for work in government offices on African-wear Fridays, or simply as everyday clothing. A fraction of shops also produce ready-made garments or supply larger school uniform contracts, but exporting or selling to large distributors is rare.

The typical firm in our context is firm size one, with only the owner of the firm supplying labor. However, a large fraction employ apprentices or somewhat better paid piece rate workers who have completed an apprenticeship through that widespread informal institution. The production technology for these firm owners consists of a mix of hand or foot-crank sewing machines that do not require electricity, and electrically-powered embroidery, overlock, and sewing machines. Some firm owners have no electricity connection and all and/or rely exclusively on hand or foot powered machinery, whilst others rely exclusively on tools or machinery requiring electricity access to function. Variation in reliance on electricity is also seen in other informal manufacturing trades, such as cosmetology, welding, carpentry and masonry.

3 Hohoe Garment Maker Study

Data collection took place in Hohoe Municipal District, a mountainous part of the Volta Region in Eastern Ghana near the border with Togo. In February of 2014, we conducted a census of all garment making firm owners in the district in preparation for this and other projects, a listing which included 1,024 active garment making firm owners. The activity began with existing lists of firms provided by the leadership of the local chapter of the Ghana National Tailors and Dressmakers Association (GNTDA) and other local trade associations, and continued through snowball sampling until all leads were exhausted. Our field staff then conducted a final stage of geographic road-by-road canvassing.

Individuals were included in the sample if they met three criteria. First, they had to report the ability to produce at least one of three commonly sold bespoke garment products: a man's shirt, a woman's slit and kabbah (a fitted top and long skirt), or a captan (the attire traditionally worn by Ghanaians from the Northern part of the country). Second, they had to report owning a garment making business, though the business need not have a permanent physical location. Third, they had to report that the business was currently operational or was planned to be in operation over the next year.

3.1 Hohoe Town Sample

Data collection for the weekly monitoring data, which we use to construct the daily and weekly panel, was restricted to the portion of the census sample geographically located in Hohoe town, the district capital, and its outlying suburbs. The sample restriction was motivated both by logistical considerations and the need to isolate a separable portion of the firm owner relationship network for this paper's parent project (Hardy and McCasland, 2016). The Hohoe town sample included 445 firms from the census. Of these, 417 were still operational in Hohoe town at the time of the weekly monitoring surveys in March and April of 2015, and of these, 343 reported having any electricity connection to their shop or place of business at the time of the baseline survey in June 2014. These 343 firms make up our analysis sample.

3.2 Defining an Operational Firm

Specifications presented in the paper exclude weeks during which the firm owner reported no sales, no orders, no expenses, no owner hours, and no worker hours, as we interpret these as inactive or not operational weeks. Seven firms in our analysis sample are not operational for all of the seven weeks of the weekly monitoring data collection, primarily due to maternity leave. An additional 111 firms in the sample are not operational by this definition in at least one of the seven weeks in the weekly monitoring data, for a total of 267 not operational weeks (11% of the weeks in the data). The main reasons cited for inactivity are travel and illness, though we cannot rule out other explanations endogenous to electricity availability (such as lack of demand or other work opportunities).

Incidentally, the March/April 2015 time period of the weekly monitoring data falls during Easter, a period of frequent travel in Ghana[3]. Part of this timing was by design (Easter is a period of heavy activity), but it also leads to a potentially larger than average number of zeros in the weekly data. Some inactivity may also be due to the fact that our original sample criteria defined a garment making firm owner relatively loosely.

3.3 Data

Data collected for this paper was primarily intended for the parent project's experimental follow-ups, making it less than ideal is some instances. The advantage, however, is that we are able to draw from many different data sources over the course of two years in the analysis.

[3]Holiday periods are often marked by funerals, which are important cultural events in Ghana. Scheduling funerals around holidays and festivals allows visiting family, friends, and community members to also attend. These funerals can end up extending the period of any Easter related travel.

3.3.1 Census

The census data, collected in February 2014, includes the GPS location of the shop or place of business. It is also our only source of data on the job title of employees in the firms in our sample. 49% of our analysis sample of firms report any workers in their business at the time of the census, and about 46% of firms report positive worker hours during our weekly monitoring data collection. At census, workers were recorded as either apprentices (low paid worker trainees; 72% of all workers in the sample), paid workers (who have completed an apprenticeship and are typically paid a piece rate of one third of the sale price; 20% of all workers in the sample), or unpaid family workers (a bit less than 8% of all workers in the sample). We use these classifications to test heterogeneity results differentiated by whether the firm employed any of each type of worker at baseline (as a proxy for availability of that type of worker during the lights crisis). All later data collection uses an alternative worker classification (permanent or temporary workers) which is generally lumped together as workers and worker hours in the analysis.

3.3.2 Baseline Survey

The baseline survey was conducted with 982 of the 1,024 firms listed in the census in June of 2014. We use the firm owner characteristics captured in the demographic, cognitive, firm history, and managerial skills modules of the survey to test our identifying assumptions and to inform subgroup analysis. Baseline capital stock in electric and non-electric equipment is used to test for changes in generator and other investment.

In addition, the baseline survey included a lengthy network map of all connectivity between firm owners in the Hohoe town sample. The strategy for data collection prompted firm owners to list connections they may have from various sources (former apprentices, neighbors, trade association members, etc.) and asked about relationships along several dimensions (including technology sharing, price discussions, loans and gifts, and simply sharing greetings). We use this network data to measure spillovers and coping strategies associated with the lights crisis.

3.3.3 Weekly Monitoring

The 445 firms in the Hohoe town census sample were cluster randomly assigned by neighborhood to weekdays for weekly monitoring surveys, in an effort to spread daily recall randomly across days (if, for example, the weekend interlude makes it easier or harder to recall certain information). Data collection began on Thursday, March 5th, 2015, referencing daily blackout and hours worked recall for Thursday, February 26th through Wednesday, March 4th, and weekly sales, orders, and expenses recall for that same seven day period. The first day in the data is thus Thursday, February 26th. The four other weekday survey groups were started on Friday, March 6th, Monday, March 9th, Tuesday, March 10th, and Wednesday, March 11th. Data collection continued in this weekly manner through to Wednesday, April 22nd, 2015. Field staff conducted make-up surveys for missed days where possible, though these referenced the originally intended seven day period for that survey. The final make-up survey was conducted on May 8th, 2015[4].

Due to the overlapping seven day structure, there are a total of 55 possible days covered in the daily panel, with 43 fully overlapping days. Day fixed effects correspond to the actual date. Week level specifications control for week by day code fixed effects, a combination of the ordered weeks one through seven, and the day of the week that the firm was randomized to for survey purposes. This ensures that we control not only for the ordered week, but for the exact same seven day period across firms.

Weekly monitoring data includes the majority of the key variables in our analysis, including blackout days, hours worked by the firm owner and other workers, and weekly sales, orders, and expenses.

3.3.4 Long-term Equipment Follow-Up

Data on equipment stock come from a follow-up conducted for the parent project in June of 2015.

[4] In our analysis sample of 343 firms, we targeted a total of 2,401 surveys (343 by 7 weeks). 38 of these are simply missing (as opposed to reported as not operational by the definition above), primarily due to travel by the firm owner towards the end of the data collection period.

3.3.5 ECG Lights Off Schedules

Although we observe significant variation in blackout reporting by day in the analysis sample, the official ECG load shedding schedules list Hohoe town in 2015 as a single grid with a single rationing schedule. We obtained copies of the ECG log books for all but the last four days in our data, and use these to run robustness checks on our main specifications. We explore the disagreement between firm reported blackouts in our data and the ECG schedules in the identification section below[5].

3.3.6 Tranformers Data

Our field team conducted a census of all electricity transformers, from which individual electricity connections stem, in November of 2016. Though it appears firm owners in our sample are unable to determine the transformer their connection stems from, we use this data combined with GPS data from the firm census to match firms to transformers by distance in robustness checks. There are 24 transformers in the data.

3.3.7 Measuring Profits

Baseline survey measures of profits and revenues use single question monthly self-reports of profits and revenues as in previous work (Hardy and McCasland, 2015). These measures appear in summary statistics and balance tables.

The weekly monitoring data collected revenues by garment type and expenses by type, without any summary measure of profits reported directly. One advantage of this strategy is that it allows us to generate weekly rather than monthly measures to create a longer panel. In addition, we found that it was faster to collect these pieces than to ask a single summary question on a weekly basis. Another advantage is that self-reported profits are frequently de facto censored at zero, as firm owners rarely report negative profits. Using reported sales and expenses to ex post calculate profits allows for the entire distribution of possible profit levels. On the other hand, many expenses are paid on a monthly, bi-annual, or annual basis, making weekly measures including them noisy, and other work on measuring profits has recommended summary questions as potentially more accurate noisy measures (De Mel, McKenzie and Woodruff, 2009).

[5]Given the political sensitivity of the Dumsor crisis, repeated attempts to obtain more detailed information on the grid structure and power availability have been met with resistance.

Expenses reported in our weekly monitoring surveys are as follows: electricity bills, rent, taxes, wages, outsourcing fees, inventory, furniture, machinery, tools, repairs, and other. In the specifications presented below, we calculate profits as total sales less total expenses.

3.4 Sample Characteristics

Table 1 presents baseline characteristics for the 343 firms in the analysis sample. The sample is a set of mostly informal businesses, run by people with nine years of schooling (the end of free and compulsory education in Ghana). The mean firm size is 2.13 including the owner, though only about half of the firms in the sample have any workers besides the owner. Profits in these firms average about 150 GhC per month, which at the time of the baseline survey was approximately 50 USD. 26% of firms are owned by men, a share that is larger than the full Hohoe Town sample because men are more likely to have an electricity connection.

Management practices are the following: keeps written business records, keeps written inventory records, knows input costs, compares prices with competitors, and uses special offers to attract customers. Over 90% of the sample knows input costs, while only about 30% keep either written business records or written inventory records. About 60% use special offers to attract customers, and about 65% report comparing prices with competitors.

Though every firm in the analysis sample reports having an electricity connection (which was later physically verified by our staff), only 75% own an electric machine. These machines include electric irons, electric sewing machines, overlock machines, and embroidery machines.

4 Identification

4.1 Across Time Variation

ECG schedules for Hohoe Town during March and April 2015 follow a 6am-6pm and then a 6pm-6am timeline, with lights off/on, on/off, on/on or off/off. In addition, they report a single load shedding schedule for the entire town. Thus in our ECG reported measures of outages, lights on variation is only across time. Much of the across time variation is related to shortages in supply meeting demand. The government has also been known to be more likely to keep lights on during holidays or other important events. For example, nearly everyone in Ghana had lights during the Africa Cup finals of 2015, when Ghana played Ivory Coast. Figures 1 and 2 show smoothed scatterplots of government reported and firm owner reported blackouts over the period of data collection against reported hours and profits. There is a clear time trend in blackouts, profits and hours worked. Note that both reported blackouts and hours fall during the time surrounding April 5th, the Easter holiday, endogenous variation in light access and working habits that we control for directly with day or week by day code fixed effects in our main specifications which focus on across-firm variation.

4.2 Across Firm Variation

Anecdotally, from the experience of the authors in the field, our research team, and firm owners in the sample, it was often the case that power was on in some parts of town, while there was an outage in another. In fact, it was often the case that one might observe lights on directly across the street or at a neighbor's shop, while one was experiencing an outage. This more haphazard outage structure is reflected in the self-reported blackout data.[6] Figures 3, 4, 5, and 6 show outages across town in four snap shot time periods on March 2nd, 2015, March 9th, 2015, March 17th, 2015, and April 10th, 2015. These figures show, as we can confirm anecdotally, that there exists both variation in average blackout level across days as well as between firms within days.

The technical foundation for this type of outage pattern depends on each firm's type of connection to transformers varying in quality, which are connected to grid lines varying in quality, which are connected to ECG substations, out of which the initial decision to supply or deny power is made. The politically charged nature of the crisis has made it difficult to officially verify the sources of this variation. Our staff conducted informal interviews with a few anonymous ECG contacts to better understand what contributes to this across firm variation:

It is the transformer that controls the electricity supply to the various [firms] in an area. The transformer is usually 3 phased (being red, yellow and blue) and a consumer may be connected to a single phase which would either be the red, yellow or blue or to a three phase which would be all three lines; red, yellow and blue.

We have something we call high-tension and it is the high tension that feeds the transformers

[6]Firm owners were given the option to report daily power access as blackout, partial blackout, or no blackout. In all specifications in the main paper, partial blackout is coded as a blackout.

and on the transformer is the receiving pot. The transformer then sends the power to various homes so if there is a cut on a particular range then what it means is that one part of an area would be off and the other on. But in a situation where the feeder (the feeder feeds/supplies power to the whole area) itself is off then the whole area would go off.

In our main specifications, we trust self-reported blackout information from firm owners and rely on within-time, cross-firm variation in blackouts. Robustness checks use firm fixed effects, consider recall error over time periods, use ECG load shedding schedules in combination with firms with no electricity access, and match firms to transformers by distance to estimate transformer level variation.

4.3 Validity of Self-Reported Blackout Data

We validate that self reported blackouts are not predicted by baseline observables conditional on date fixed effects. Table 2 presents these results for the 343 firms in our analysis sample, across the approximately 49 days per firm in the data (less observations missing due to missing surveys, "don't knows" in the blackout variable, or inactivity) using the following estimating equation:

$$Blackout_{it} = \beta_0 + \beta_1 * X_i + \epsilon_{it} \tag{1}$$

Table 2 presents the results. Firm age, firm size, and owner years of schooling appear significantly related to blackouts conditional on day fixed effects, though the point estimates are very small and economically insignificant. Other observables appear unrelated to blackout days.

4.4 Estimating Equations

Revenues, profits, orders, and expenses are recorded at the weekly level, and average treatment effects are estimated as follows:

$$Y_{it} = \beta_0 + \beta_1 * \#blackouts_{it} + \beta_2 * \#responses_{it} + \eta_{sd} + \epsilon_{it} \tag{2}$$

where $\#blackouts_{it}$ is the number of blackouts (of seven) reported in the data, $\#responses_{it}$ is the number of days for which there is a non-missing response to whether there was a blackout.[7] η_{sd} is a survey date fixed effect, constructed as week (one through seven) by survey day of the week code (Mon, Tues, Weds, Thurs, Fri). It controls for the exact seven day period covered in the survey. Our identifying assumption here is that conditional on survey date (essentially time period fixed effects), the number of blackout days reported by the firm is as good as random.

Hours, extensive margin firm owner labor supply, worker hours, and worker extensive margin labor supply is recorded on a daily basis over the seven day recall period preceding the date of each weekly survey. Average treatment effects are estimated as follows:

$$Y_{it} = \beta_0 + \beta_1 * blackout_{it} + \eta_t + \epsilon_{it} \tag{3}$$

where $blackout_{it}$ is a self-reported blackout on that date, missing blackout observations are dropped and η_t are date fixed effects. We are thus measuring the average treatment effect controlling for omitted variables fixed within day across firms. Our identifying assumption is that conditional on these fixed effects, the assignment of blackouts is not related to any omitted variables that also affect outcomes.

Equipment composition for these firms was collected retrospectively, during a follow-up survey after the study period. We have two observations of equipment composition for each firm owner, (pre and post crisis). We estimate the effect of blackouts on equipment substitution as follows:

$$Y_i = \alpha + \beta \# blackouts_i + \theta \# responses_i + \omega Y_{ib} + \epsilon_i \tag{4}$$

where Y_i is the number of equipment or machinery for firm i in June of 2015, $\# blackouts_{it}$ are the total number of blackout days reported during the survey period by firm i, $\# responses_{it}$ are the total number of days for which firm i reported either a blackout or no blackout during the survey period and Y_{ib} is the number of equipment or machinery for firm i in June of 2014.

All errors in the main specifications are clustered at the neighborhood level, as the day of the survey randomization was clustered by neighborhood. There are 23 neighborhood clusters in the sample.

Note also that the use of cross-firm variation means that we are not estimating the effects

[7] Missing blackout responses come from about 15% coded as "don't remember".

of blackouts when in fact the entire town had a blackout (as laid out in the ECG load-shedding schedules). Thus our estimates are an underestimate of the total negative effects of the lights crisis on firms.

5 Main Results

5.1 Weekly Effects of Blackouts

Table 3 shows our estimated weekly effects of blackout days on weekly completed orders, revenues, expenses and profits. Each additional blackout day reported is associated with .42 fewer orders completed and 5.43 GhC less in revenues. Firm owners reduce weekly expenses by 1.67 GhC for each blackout day, leaving them with 3.75 GhC less profits per blackout day. These are large results in magnitude, considering that average weekly profits, sales and completed orders during this period are 34.55 GhC, 67.71 GhC and 8.16 respectively.

Table 4 unpacks the decrease in expenses by category. The coefficient on number of blackout days is negative for all expenditure types, but the only significant coefficient of number of blackout days is for wages. The largest magnitude coefficient of number of blackout days is for inventory expenditure. Combined with further results presented below, we interpret the coefficient on wages as a sign that paid workers were sent home during blackout weeks, and firms substituted instead to lower paid apprentice labor where possible. Contextually, this type of substitution would make sense because paid workers function more directly as firm owner substitutes, working more on electric machines and doing more complex tasks. Apprentices typically work on hand and foot crank sewing machines, and are a relatively inexpensive alternative to quicker (and more precise) production on electric machines. We cannot, however, pin down this substitution due to data constraints. As mentioned above, our weekly monitoring data does not specify the job title of workers when asking about wages and hours worked.

5.2 Effects of Blackouts on Equipment and Machinery

Table 5 explores the overall effects of blackout days on equipment substitution. We do not see any significant equipment substitution in response to blackout days, other than a very small significant effect on the number of generators owned at .003 generators per blackout day. While the sign is encouraging that this data is high quality, with less than 3% of our sample owning a generator, this effect is even not economically meaningful. This lack of equipment substitution could be due to inefficient capital or credit markets, or due to the unpredictability of future periods of frequent blackouts.

5.3 Daily Effects of Blackouts

Table 6 explores the daily effects of blackouts on labor supply. A blackout decreases owner hours by approximately half an hour (.47) and decreases the likelihood of the owner coming to work at all by 4%. Point estimates on worker labor supply are not significant in the main specification.

In Tables 7 and 8, we explore how this labor supply response varies across days of the week. We find that firm owners are most responsive on Tuesday, Wednesdays, Thursdays, and Saturdays. These findings accord with contextual information from the field. First, garment makers in this largely Christian part of Ghana almost never work on Sundays (whether or not there is a blackout). Second, Mondays are typically cutting days, in which garment makers cut fabric for designs to be produced during the week, a task that does not require the use of an electric machine (although actual light might be helpful, many garment makers could simply put a table outside and use natural light for that purpose). Finally, a large response on Saturdays accords with the typical work schedule, as many garment makers only work on Saturday as needed. The available of this "flex day" may help firms ameliorate the effects of the blackouts by moving labor supply only Saturday when there is electricity on a Saturday.

Table 9 considers this labor supply flexibility across days, by looking at how firm owners shift labor supply from a day with blackouts onto a day without a blackout. Results are presented for three scenarios: (1) days with a blackout, when there was no blackout yesterday, (2) days with lights, on which the firm owner reported a blackout yesterday, and (3) days with a blackout, on which the firm owner also reported a blackout yesterday. These are all compared to days with lights, in which the firm owner reported that there were also lights yesterday. In this sample, we restrict the days to Tuesday through Friday, so that we are looking at pairs of days that fall in the normal working schedule. Again, we validate that firm owners reduce working hours and the probability of working on days with blackouts. However, we also see that they reduce them even further when blackouts persist throughout a week (a nod to the fact that the production process is stalled). We also see that firm owner increase hours on days with lights following a blackout day, but do not fully compensate for hours losses on blackout days. This incomplete flexibility is an interesting feature of firms in which the primary input in owner labor. While raw materials can be shifted across periods of higher or lower productivity, firm owner hours can only shift so much across days.

5.4 Labor Productivity

In a fairly simple measure of labor productivity, simply profits over owner hours worked and wages over worker hours worked, we see that blackouts in a week are associated with negative point estimates. This finding is unsurprising, and fits with the remainder of the story. Results are presented in Table 10.

6 Robustness Checks

6.1 Firm Fixed Effects

While it appears our daily self-reported blackout day measures are unrelated to firm characteristics, we have the power to include firm fixed effects in daily level specifications. These specifications would control for any time fixed firm characteristics that affect the self-reported blackout measure. Table 11 presents the results. Point estimates on firm owner hours worked and firm owner work at all are remarkably stable between Tables 6 and 11. This finding further validates the self-reported data.

6.2 Recall Period

Another alternative specification restricts the daily sample to questions about yesterday. Specifically, for example, labor supply questions about Monday, asked in a survey conducted on Tuesday. Given that surveys were only conducted on Monday through Friday, this sample only includes Monday, Tuesday, Wednesday, and Thursday (while all preceding specifications include all five days). Again point estimates on firm owner hours worked and firm hour extensive margin go in the same direction. Results are presented in Table 12.

Point estimates on worker hours and worker extensive margin labor supply are positive and significant in this specification, further suggestive evidence, we believe, that apprentice labor hours respond on Mondays through Thursdays.

6.3 ECG Load Shedding Schedules

Table 13 presents the result from a specification of the following form:

$$Y_{it} = \beta_0 + \beta_1 * access_i + \beta_2 * ECG_t + \beta_3 * access_i * ECG_t + \eta_{week} + \epsilon_{it} \tag{5}$$

where access is a dummy for whether the firm reported having electricity access at baseline, and ECG is a dummy for whether the ECG load shedding schedule reported lights out on that day. η_{week} are week fixed effects. Errors are clustered at the neighborhood level. All specifications drop Saturday and Sunday, as the ECG schedules are far more likely to report blackouts on Saturdays and Sundays (by design).

We see that the point estimates for labor supply decrease among firms with electricity is remarkably similar to the self-reported data, suggesting that some of the total variation in blackouts is explained by the ECG load shedding schedules. In this case we are likely measuring a noisy estimate of blackouts that affected all of Hohoe town, a different source of variation than that isolated in the across-firm self-reported variation. It is thus reassuring that the point estimate is so similar, and that we only find a reduction in labor supply associated with a blackout for firms with baseline electricity access.

6.4 Matching Firms to Transformers

Figure 7 plots an example date with the 24 transformers identified in the transformer census. We match firms with non-missing GPS data to the closest transformer by distance, and reassign blackout to a value of one if 75% of the firms in that transformer and date report a blackout or a partial blackout and to a value of zero if fewer firms than 75% of the firms in that transformer and date report a blackout or a partial blackout. We then re-run our main specifications at the weekly and daily level.

These specifications aggregate blackouts to the transformer level in a somewhat ad hoc way, potentially adding noise to the data, but also allowing us to run regressions using something closer to the true source of the variation across firms. It is reassuring that the findings follow essentially the same pattern as the self-reported data. Namely, labor supply hours and extensive labor supply go down for firm owners experiencing a blackout. Weekly revenues and profits have negative point estimates on the number of days in a week with a blackout, and the revenues point estimate is statistically significant. Results are presented in Tables 14 and 15.

7 Heterogeneous Impacts

Tables 16 and 17 explore the heterogeneous impacts of blackout days on firm inputs and outcomes over four characteristics: any apprentices at baseline, any paid workers at baseline, any unpaid workers at baseline, and the % of baseline equipment and machinery requiring electricity[8]. Having apprentices attenuates the effects of blackouts, while having paid workers and electricity intensive equipment exacerbates the effects. Having unpaid workers does not appear to alter the effects of blackouts.

Here, again, we interpret this finding in light of contextual knowledge about the production process. Apprentices earn low wages and typically work on hand and foot crank machines. This is thus suggestive evidence that firm owners are able to shift some work from electric machines to apprentices where apprentices are available, and that firms with paid workers may find it difficult to adjust (as they may be more reliant in their normal production process on paid workers working on electric machines).

7.1 Spillover Effects

Tables 18 and 19 explore spillover effects of network blackouts on firm inputs and outcomes. Blackout days have larger effects when a firm owner's entire network also experiences a blackout. This finding suggests that network connected firms provide an insurance function in the face of unreliable infrastructure. It may be the case that inter-connected nature of business in low-income countries is driven at least in part by the need for this insurance function, much as households mutually insure each other in places with lacking credit markets and large income shocks. These findings

[8]This % is calculated by dividing the number of equipment or machinery requiring electricity by the total number of equipment or machinery owned by the firm owner in June of 2015.

match anecdotal evidence from firm owners that "borrowing" electricity (i.e. working for a short period on another firm owner's machine) was one response to the crisis.

8 Conclusion

Some of the most basic infrastructure for private sector firms is deeply unreliable in poor countries. Ghana, despite its large-scale hydropower projects built shortly after independence, is no exception. In this paper we study the effects of blackouts on small firms, the most common firm type, and the sector of the economy that employs the most people in Ghana. The negative impacts of outages on production are economically meaningful and statistically significant.

Our findings also document firm-level coping strategies for dealing with unpredictable and unreliable energy access, including substituting owner labor across time, reducing expenditure, accessing network spillovers in energy access, and the use of substitutes to electrically-powered capital (apprentices). Despite myriad coping strategies, profits fall significantly as a result of energy shortages in most firms. We explore heterogeneity in these effects, and conclude that, as might be expected, firms that employ paid workers and electric equipment suffer more than those that use less electric equipment or have access to low-paid apprentices. It is also the case that firms with larger paid workforces and more electric equipment relative to human-powered equipment are those that are larger and more profitable. This could suggest that infrastructure problems affect exactly those firms that have more potential for growth. Nonetheless, even firms of size one do not fully substitute work hours across days, and thus suffer losses.

While our study focuses on short term losses and the short term nature of coping strategies, more work on the effects of infrastructure on firms is needed. How do periods of electricity crisis affect the extensive margin of firms entering or exiting the market? How do small firms cope in the long run? We leave these questions for future research.

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Figure 1: **Locally Weighted Scatterplot Smoothing - Blackouts and Hours Over Time**

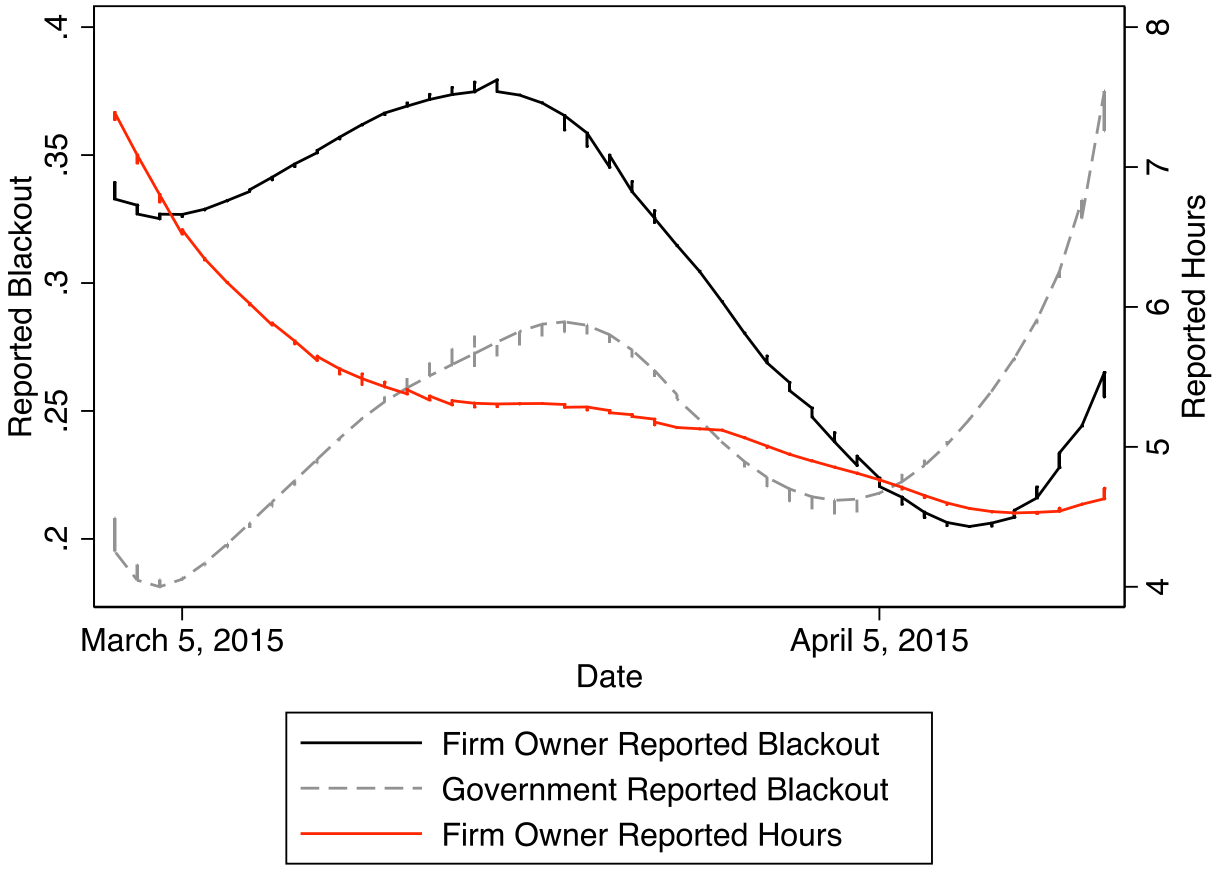


Figure 2: **Locally Weighted Scatterplot Smoothing - Blackouts and Profits Over Time**

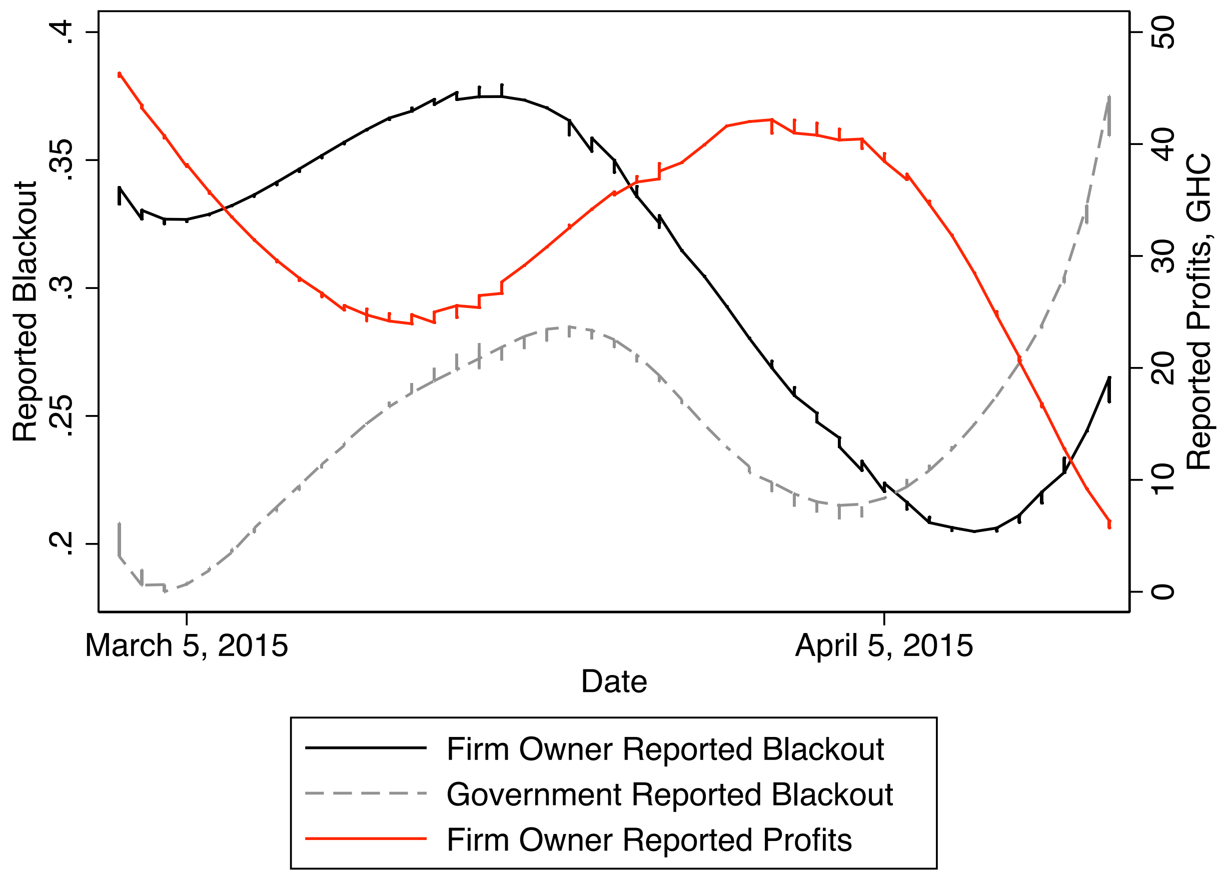
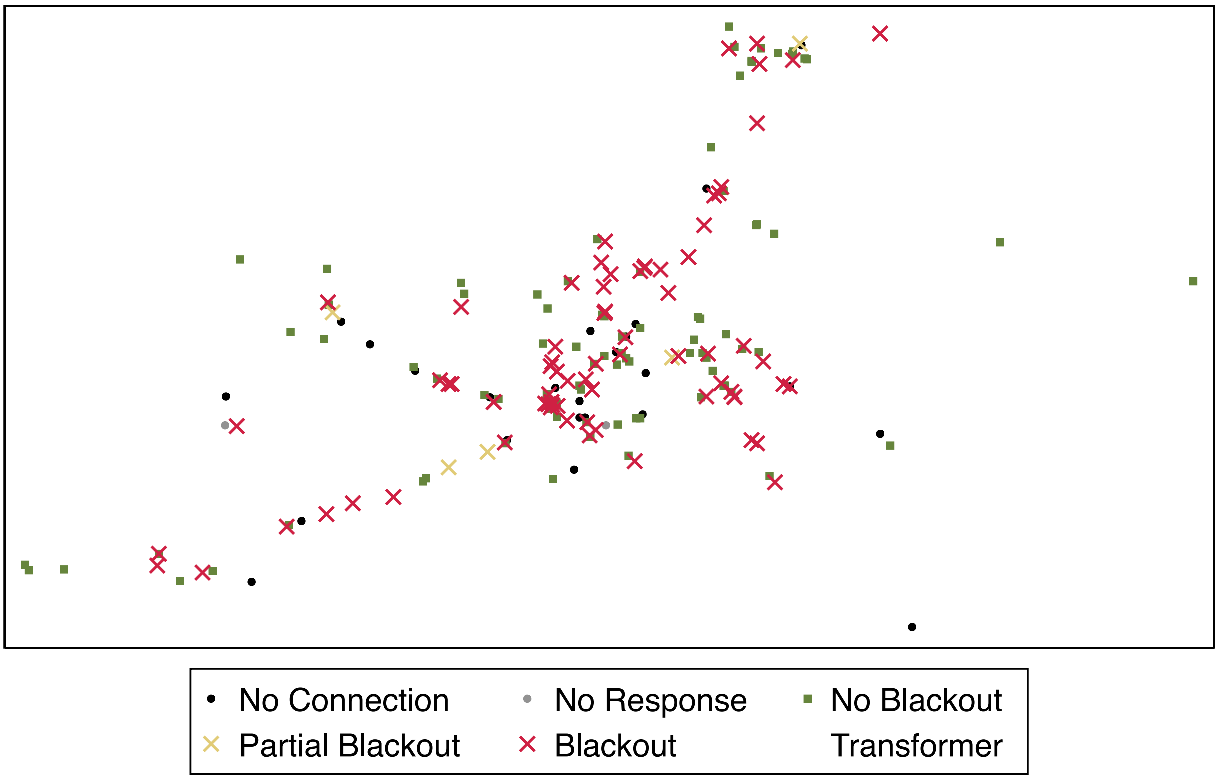
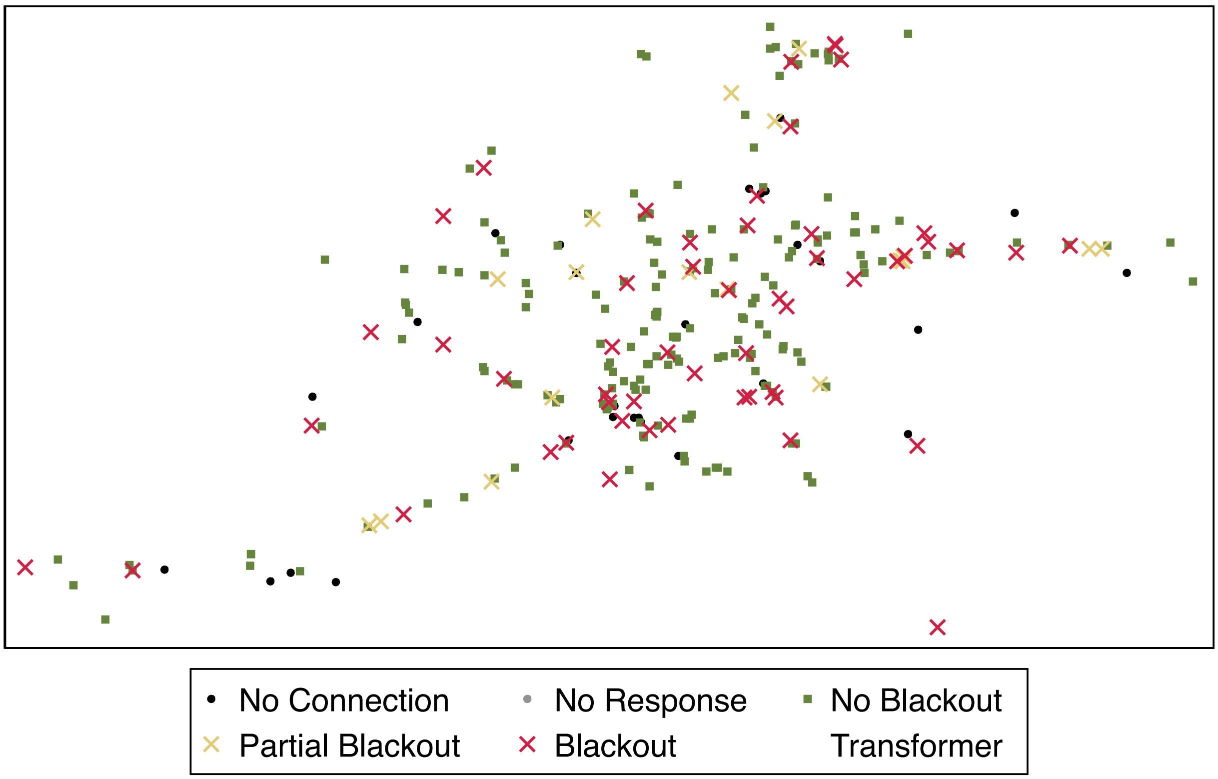


Figure 3: **Example Geospatial Blackouts Scatterplot - March 2nd, 2015**



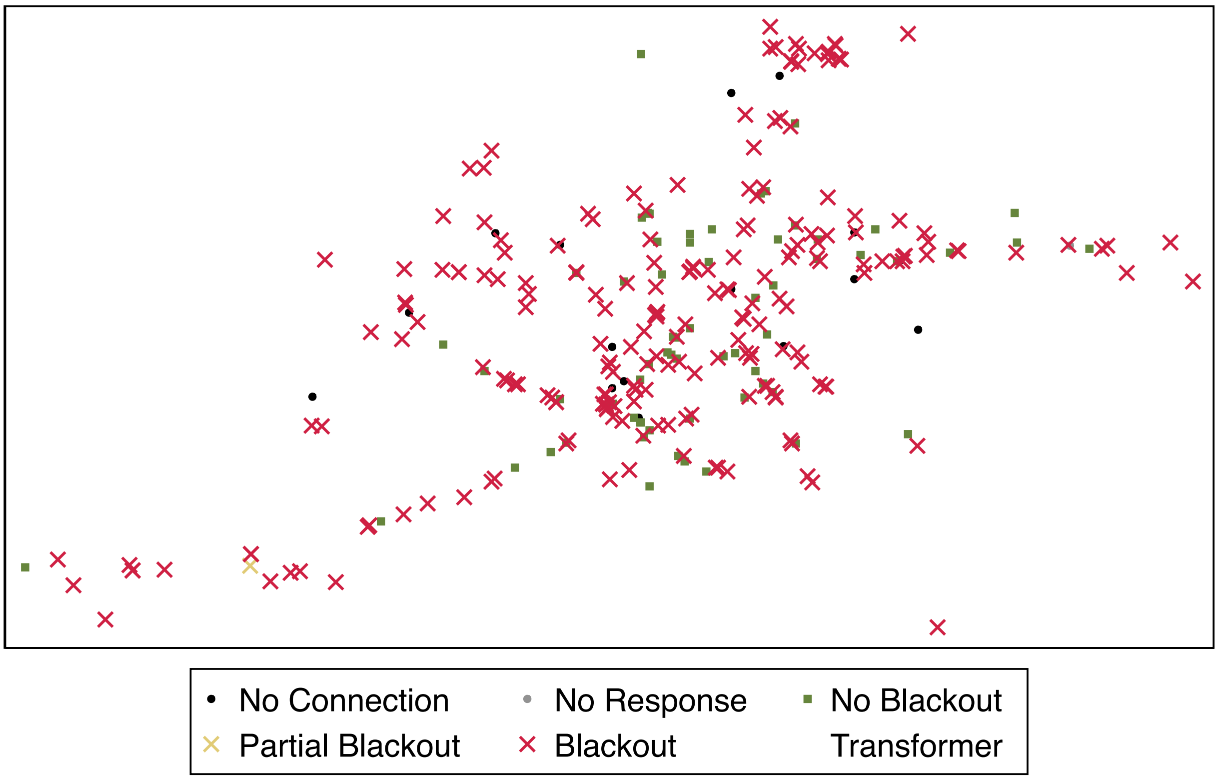
Note: Less densely populated areas have been omitted to prevent overlap and aid in visualization.
To protect the privacy of our sample, all coordinate values have been slightly adjusted,
a few values have been omitted and axis labels have been removed.

Figure 4: **Example Geospatial Blackouts Scatterplot - March 9th, 2015**



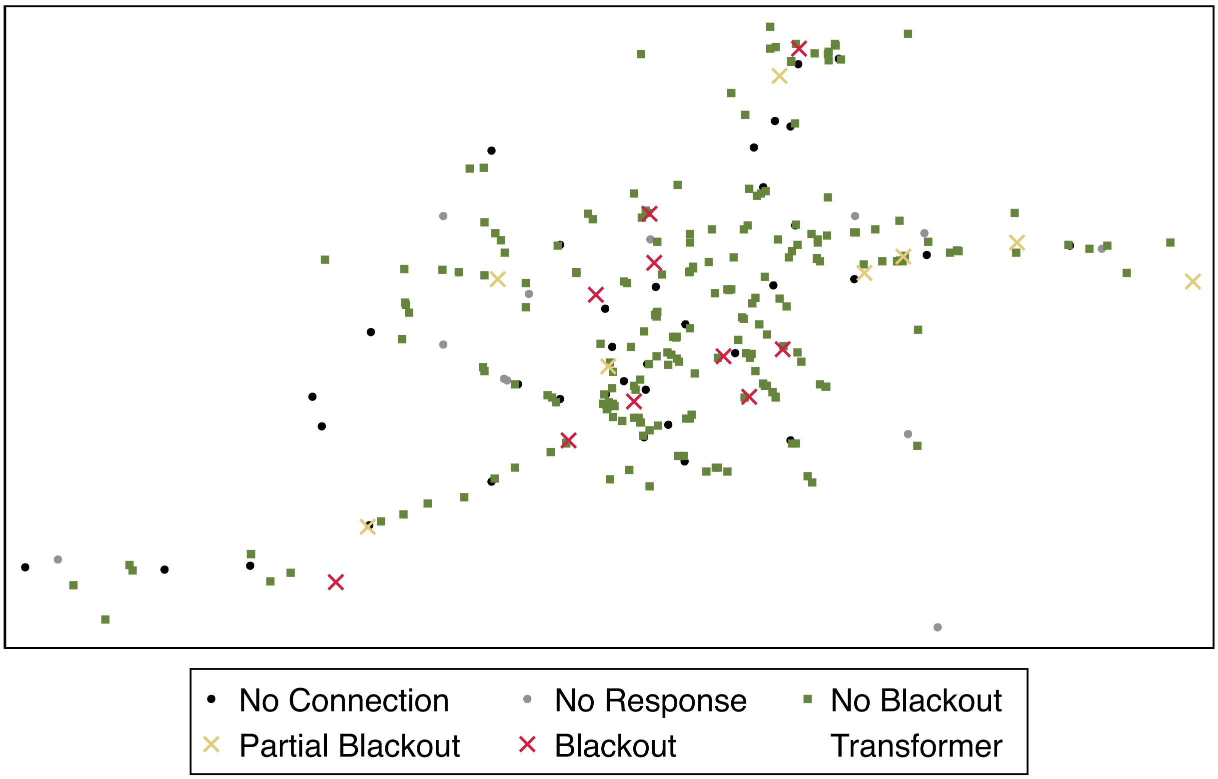
Note: Less densely populated areas have been omitted to prevent overlap and aid in visualization.
To protect the privacy of our sample, all coordinate values have been slightly adjusted,
a few values have been omitted and axis labels have been removed.

Figure 5: **Example Geospatial Blackouts Scatterplot - March 17th, 2015**



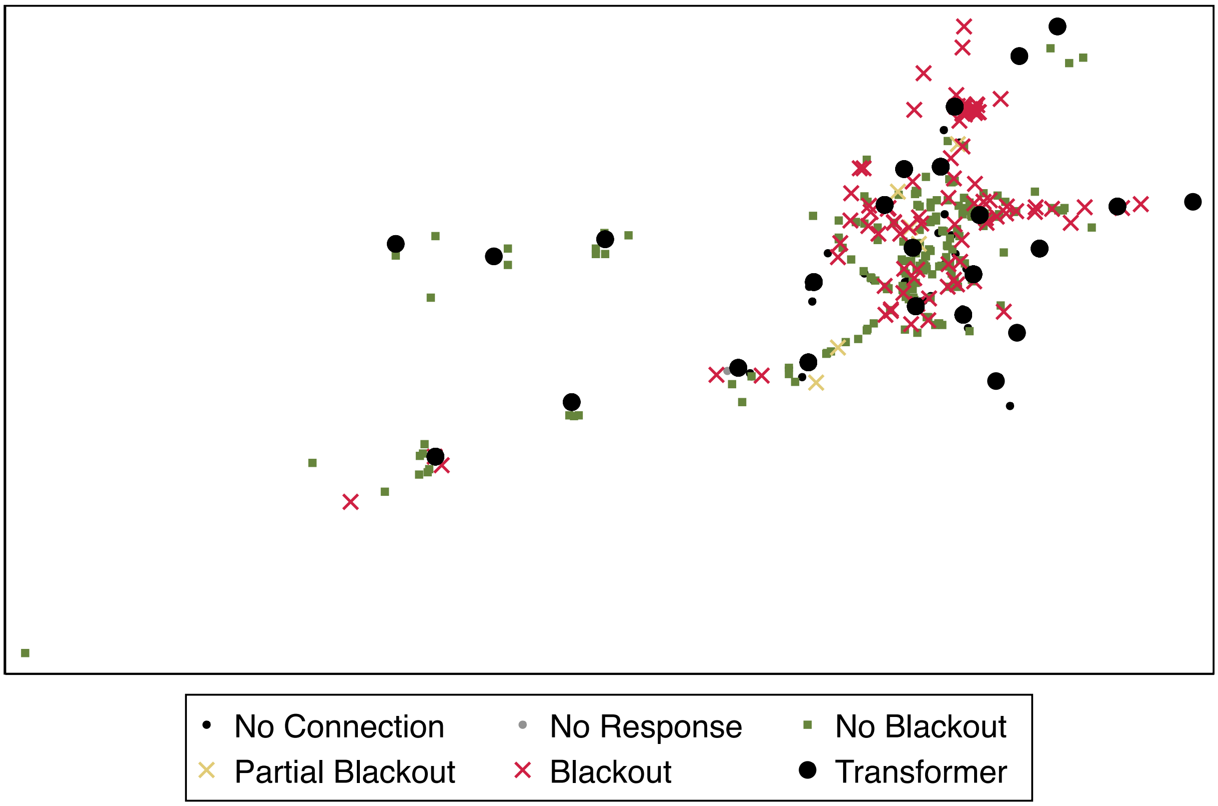
Note: Less densely populated areas have been omitted to prevent overlap and aid in visualization. To protect the privacy of our sample, all coordinate values have been slightly adjusted, a few values have been omitted and axis labels have been removed.

Figure 6: **Example Geospatial Blackouts Scatterplot - April 10th, 2015**



Note: Less densely populated areas have been omitted to prevent overlap and aid in visualization.
To protect the privacy of our sample, all coordinate values have been slightly adjusted,
a few values have been omitted and axis labels have been removed.

Figure 7: **Example Geospatial Blackouts Scatterplot with Transformers - March 27th, 2015**



Note: To protect the privacy of our sample, all coordinate values have been slightly adjusted, a few values have been omitted and axis labels have been removed.

Table 1: **Summary Statistics and Sample Selection**

	Survival Selection			Electricity Sample Selection			Firms with Electric Machines		
	Leavers	Survivors	Diff	Survivors w/out Access	Survivors w/ Access	Diff	Sample w/out Machines	Sample w/ Machines	Diff
Male	0.14	0.23	-0.08	0.08	0.26	-0.18***	0.15	0.30	-0.14**
Ewe ethnicity	0.75	0.76	-0.01	0.69	0.77	-0.08	0.78	0.77	0.01
Years schooling	8.93	8.85	0.08	8.65	8.90	-0.25	8.83	8.92	-0.10
Ravens score (of 12)	5.68	5.63	0.05	5.19	5.72	-0.53	5.34	5.85	-0.51
Owner age	31.29	35.53	-4.24*	34.93	35.66	-0.73	35.53	35.71	-0.18
Firm size (including owner)	1.79	1.99	-0.20	1.38	2.13	-0.75***	1.64	2.31	-0.67**
Has any worker(s) besides owner	0.32	0.47	-0.15	0.23	0.52	-0.30***	0.33	0.59	-0.27***
Revenues (GhC)	148.07	196.72	-48.64	111.73	215.11	-103.38***	153.30	235.87	-82.56**
Profits (GhC)	106.11	138.01	-31.90	74.74	151.70	-76.95***	116.40	163.55	-47.16*
Assets excl land/building (GhC)	768.18	1214.26	-446.09	544.01	1358.87	-814.85***	848.00	1529.82	-681.82**
Management practices (of 4)	2.36	2.32	0.04	2.20	2.34	-0.14	2.07	2.44	-0.37**
Firm age	5.64	9.49	-3.85*	8.72	9.67	-0.95	8.50	10.10	-1.60
Trade association member	0.07	0.22	-0.15	0.11	0.24	-0.14*	0.12	0.29	-0.17**
Registered w/any govt agency	0.07	0.17	-0.09	0.05	0.19	-0.14**	0.15	0.20	-0.05
Electricity access	1.00	0.82	0.18*	0.00	1.00	-1.00	1.00	1.00	0.00
Has any electricy machines	0.00	0.66	-0.66***	0.27	0.75	-0.48***	0.00	1.00	-1.00
Observations	28	417		74	343		86	257	

Table 2: **Linear Regression of Blackouts on Firm (Owner) Characteristics**

Regressor	(1) Male	(2) Ewe ethnicity	(3) Years schooling	(4) Ravens score (of 12)	(5) Owner age
Coefficient	0.011	0.003	-0.006*	-0.002	-0.001
	(0.009)	(0.028)	(0.003)	(0.001)	(0.000)
Average Value of Regressor	0.277	0.771	8.916	5.802	35.883
Observations	13,194	13,194	12,295	13,194	12,295
R-squared	0.000	0.000	0.001	0.000	0.000

Regressor	(6) Firm Size (w/ owner)	(7) Has any worker(s) (besides owner)	(8) Revenues (GHC)	(9) Profits (GHC)	(10) Assets excl land/building (GHC)
Coefficient	0.005**	0.010	0.000	0.000	0.000
	(0.002)	(0.013)	(0.000)	(0.000)	(0.000)
Average Value of Regressor	2.206	0.527	228.485	161.247	1392.453
Observations	12,247	12,247	13,152	13,152	13,194
R-squared	0.000	0.000	0.000	0.000	0.000

Regressor	(11) Management practices (of 4)	(12) Firm age	(13) Trade Assocation Member	(14) Registered w/any govt agency	Has any electric machine
Coefficient	0.000	-0.001*	-0.003	-0.004	0.010
	(0.003)	(0.001)	(0.013)	(0.012)	(0.013)
Average Value of Regressor	1.949	9.981	0.260	0.204	0.828
Observations	13,194	12,295	13,107	13,152	12,372
R-squared	0.000	0.000	0.000	0.000	0.000

Note: Average value of blackout (outcome variable) is .31. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Weekly Effects of Blackouts**

VARIABLES	(1) Weekly Orders (Completed)	(2) Weekly Revenues (GhC)	(3) Weekly Expenses (GhC)	(4) Weekly Profits (GhC)
# Blackout Days	-0.42**	-5.43***	-1.67***	-3.75**
	(0.16)	(1.92)	(0.57)	(1.77)
# Days Responding	0.44**	4.99***	1.24*	3.76***
	(0.16)	(1.24)	(0.62)	(0.85)
Average Value of Outcome Variable	8.16	67.71	33.16	34.55
Observations	2,096	2,096	2,096	2,096
R-squared	0.076	0.126	0.062	0.086

Note: All regressions include time fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Weekly Effects of Blackouts on Expenses**

VARIABLES	(1) Wages	(2) Out-sourcing	(3) Inventory	(4) Bills	(5) Repairs	(6) Invest-ment
# Blackout Days	-0.33**	-0.23	-0.48	-0.29	-0.06	-0.40
	(0.12)	(0.31)	(0.44)	(0.24)	(0.32)	(0.36)
# Days Responding	0.40**	0.16**	0.75**	0.05	-0.13	0.12
	(0.15)	(0.07)	(0.27)	(0.11)	(0.20)	(0.21)
Average Value of Outcome Varia	3.04	4.47	5.68	15.48	1.29	1.16
Observations	2,095	2,096	2,095	2,096	2,096	2,096
R-squared	0.026	0.044	0.066	0.052	0.030	0.015

Note: All regressions include time fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Effect of Blackouts on Equipment/Machine Composition**

	Number of Equipment/Machines in June, 2016								
VARIABLES	(1) Generators	(2) Inter-locking Machine	(3) Embroid-ery Machine	(4) Industrial Sewing Machine	(5) Electric Sewing Machine	(6) Foot-crank Sewing Machine	(7) Hand-crank Sewing Machine	(8) Electric Irons	(9) Coal Irons
Blackout Days Reported	0.003*	-0.004	0.003	0.002	-0.001	-0.006	0.003	-0.007	-0.001
(Total #)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.009)	(0.008)	(0.006)
Days Reported	-0.000	0.001	-0.001	-0.000	0.004*	0.006**	0.001	0.003	0.003
(Total #)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)	(0.003)	(0.003)
June, 2015	0.611***	0.857***	0.897***	0.987***	0.898***	0.869***	0.755***	0.764***	0.641***
(# Equipment/Machines)	(0.180)	(0.040)	(0.046)	(0.006)	(0.023)	(0.053)	(0.072)	(0.066)	(0.059)
Average # June, 2015	0.026	0.178	0.094	0.071	0.579	0.518	1.058	0.838	0.841
Observations	309	309	309	309	309	309	309	309	309
R-squared	0.519	0.791	0.825	0.848	0.822	0.793	0.617	0.561	0.388

Note: Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: **Daily Effects of Blackouts on Labor**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout Reported	-0.47***	-0.04***	0.30	0.03
	(0.11)	(0.01)	(0.27)	(0.03)
Average Value of Outcome Variable	5.46	0.62	6.10	0.65
Observations	13,194	13,194	13,194	13,194
R-squared	0.384	0.422	0.064	0.065

Note: All regressions include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Daily Effects of Blackouts on Owner Hours Worked by Weekday**

VARIABLES	Monday # Hours Worked	Tuesday # Hours Worked	Wednesday # Hours Worked	Thursday # Hours Worked	Friday # Hours Worked	Saturday # Hours Worked	Sunday # Hours Worked
Blackout Reported	-0.30	-0.87***	-0.46**	-0.49***	-0.35	-0.81***	0.08
	(0.33)	(0.16)	(0.22)	(0.16)	(0.24)	(0.22)	(0.11)
Average Value of Outcome Variable	6.793	7.329	7.649	7.596	7.144	2.536	0.202
Observations	1,899	1,898	1,894	1,895	1,923	1,849	1,836
R-squared	0.090	0.045	0.031	0.020	0.016	0.035	0.009

Note: All regression include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. ***p<0.01, **p<0.05, p<0.1.

Table 8: **Daily Effects of Blackouts on Extensive Owner Labor Supply by Weekday**

VARIABLES	Monday Worked	Tuesday Worked	Wednesday Worked	Thursday Worked	Friday Worked	Saturday Worked	Sunday Worked
Blackout Reported	-0.02	-0.07***	-0.02	-0.03	-0.05	-0.09***	0.01
	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)
Average Value of Outcome Variable	0.764	0.827	0.868	0.861	0.802	0.3	0.036
Observations	1,899	1,898	1,894	1,895	1,923	1,849	1,836
R-squared	0.088	0.033	0.025	0.014	0.013	0.032	0.006

Note: All regression include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. ***p<0.01, **p<0.05, p<0.1.

Table 9: **Lagged Daily Effects of Blackouts on Labor**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout Reported Today Only	-0.42***	-0.03**	0.25	0.03
	(0.13)	(0.01)	(0.44)	(0.04)
Blackout Reported Yesterday Only	0.18*	0.02**	0.54	0.05
	(0.10)	(0.01)	(0.50)	(0.05)
Blackout Reported Both Today and Yesterday	-0.69***	-0.05**	0.42	0.04
	(0.20)	(0.02)	(1.05)	(0.12)
Average Value of Outcome Variable	7.444	0.842	8.001	0.86
Observations	7,153	7,153	7,153	7,153
R-squared	0.030	0.026	0.003	0.003

Note: All regression include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. ***p<0.01, **p<0.05, p<0.1.

Table 10: **Labor Productivity**

VARIABLES	(1) Profits per Owner Hour	(2) Wages per Worker Hour
# Blackout Days	-0.07	-0.04***
	(0.04)	(0.01)
# Days Responding	0.08**	0.02***
	(0.04)	(0.01)
Average Value of Outcome Variable	0.801	0.095
Observations	2,028	919
R-squared	0.051	0.072

Note: All regression include time fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. ***p<0.01, **p<0.05, p<0.1.

Table 11: **Daily Effects of Blackouts on Labor With Firm Fixed Effects**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout Reported	-0.46***	-0.04***	0.14	0.01
	(0.08)	(0.01)	(0.15)	(0.02)
Average Value of Outcome Variable	5.46	0.62	6.10	0.65
Observations	13,194	13,194	13,194	13,194
R-squared	0.553	0.511	0.723	0.735
Firm Fixed Effects	YES	YES	YES	YES

Note: All regressions include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: **Daily Effects of Blackouts on Labor Using Yesterday Only**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout Reported	-0.23	-0.02	2.15***	0.22***
	(0.38)	(0.03)	(0.54)	(0.06)
Average Value of Outcome Variable	7.127	0.813	7.936	0.85
Observations	1,524	1,524	1,524	1,524
R-squared	0.064	0.050	0.055	0.049

Note: All regression include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. ***p<0.01, **p<0.05, p<0.1.

Table 13: **Daily Effects of Blackouts on Labor Using Government Reported Blackouts**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Government Logged Blackout	-0.45***	-0.05***	-0.07	-0.00
	(0.13)	(0.01)	(0.12)	(0.01)
Government Logged Blackout* No electricity access	0.47*** (0.16)	0.06*** (0.02)	0.07 (0.19)	0.00 (0.02)
No electricity Access	-0.99***	-0.07***	-6.66***	-0.70***
	(0.21)	(0.02)	(1.21)	(0.13)
Average Value of Outcome Variable	5.39	0.62	5.32	0.57
Observations	11,884	11,884	11,884	11,884
R-squared	0.024	0.019	0.033	0.032

Note: All regressions include week fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: **Weekly Effects Using Transformer Level Aggregated Blackouts**

VARIABLES	(1) Weekly Orders (Completed)	(2) Weekly Revenues (GHC)	(3) Weekly Expenses (GHC)	(4) Weekly Profits (GHC)
# Blackout Days	-0.20	-4.66**	-2.66	-2.00
	(0.30)	(1.74)	(2.13)	(2.02)
# Days Responding	0.51**	4.98***	0.27	4.71***
	(0.22)	(1.26)	(1.10)	(1.20)
Average Value of Outcome Variable	7.965	65.873	32.037	33.836
Observations	1,901	1,901	1,901	1,901
R-squared	0.076	0.130	0.067	0.091

Note: All regression include time fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the transformer level. ***p<0.01, **p<0.05, p<0.1.

Table 15: **Daily Effects Using Transformer Level Aggregated Blackouts**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout Reported	-0.51***	-0.03*	-1.39	-0.13
	(0.14)	(0.01)	(0.84)	(0.09)
Average Value of Outcome Variable	5.623	0.641	5.761	0.619
Observations	12,559	12,559	12,559	12,559
R-squared	0.379	0.418	0.061	0.062

Note: All regression include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the transformer level. ***p<0.01, **p<0.05, p<0.1.

Table 16: **Heterogeneous Daily Effects of Blackouts on Labor**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout	-0.38*	-0.03	-0.35	-0.03
	(0.20)	(0.02)	(0.41)	(0.04)
Has Apprentice(s) * Blackout	0.67***	0.06***	1.22	0.12
	(0.18)	(0.02)	(0.72)	(0.08)
Has Paid Worker(s) * Blackout	-0.77***	-0.05***	-1.13	-0.14
	(0.22)	(0.02)	(1.29)	(0.13)
Has Unpaid Worker(s)* Blackout	0.12	0.01	-0.02	-0.00
	(0.18)	(0.02)	(0.63)	(0.07)
% Electric Equipment * Blackout	-0.99***	-0.09***	0.08	-0.00
	(0.30)	(0.03)	(0.58)	(0.06)
Has Apprentice(s)	0.24	0.01	9.37***	1.01***
	(0.24)	(0.02)	(1.80)	(0.19)
Has Paid Worker(s)	1.70***	0.09***	3.27	0.32
	(0.23)	(0.02)	(2.29)	(0.25)
Has Unpaid Workers	0.72**	0.05***	1.98	0.16
	(0.31)	(0.02)	(1.49)	(0.15)
% Electric Equipment	1.52***	0.07**	1.42	0.12
	(0.50)	(0.03)	(2.58)	(0.27)
Average Value of Outcome Variable	5.73	0.65	5.92	0.63
Observations	11,334	11,334	11,334	11,334
R-squared	0.409	0.432	0.214	0.215

Note: All regressions include date fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: **Heterogeneous Weekly Effects of Blackouts**

VARIABLES	(1) Weekly Orders (Completed)	(2) Weekly Revenues (GhC)	(3) Weekly Expenses (GhC)	(4) Weekly Profits (GhC)
# Blackout Days	-0.69***	-6.17***	-0.93	-5.25**
	(0.17)	(2.05)	(0.95)	(1.86)
Has Apprentice(s) * # Blackout Days	0.28	3.89**	0.88	3.00*
	(0.21)	(1.40)	(1.25)	(1.64)
Has Paid Worker(s) * # Blackout Days	-0.99***	-12.80**	-1.81	-10.99*
	(0.24)	(5.90)	(1.08)	(5.84)
Has Unpaid Worker(s)*# Blackout Days	0.10	0.13	-3.88**	4.00
	(0.29)	(2.29)	(1.80)	(2.66)
% Electric Equipment * # Blackout Days	0.04	-2.87	-3.62*	0.75
	(0.42)	(2.92)	(1.88)	(3.10)
Has Apprentice(s)	0.34	7.55	7.60	-0.05
	(0.54)	(8.95)	(4.69)	(7.19)
Has Paid Worker(s)	6.11***	87.15***	28.13***	59.02**
	(1.12)	(18.32)	(6.94)	(21.71)
Has Unpaid Workers	1.76*	10.46	11.80**	-1.34
	(0.96)	(6.59)	(5.38)	(7.47)
% Electric Equipment	3.07**	48.75***	25.12***	23.63***
	(1.44)	(8.93)	(5.92)	(7.77)
# Days Responding	0.43**	5.36***	0.91	4.44***
	(0.18)	(1.53)	(0.73)	(1.10)
Average Value of Outcome Variable	8.20	68.51	32.88	35.62
Observations	1,793	1,793	1,793	1,793
R-squared	0.119	0.198	0.112	0.115

Note: All regressions include time fixed effects. Inactive (all outcomes are zero) firm weeks are dropped. Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 18: **Spillover Daily Effects of Blackouts on Labor**

VARIABLES	(1) # Hours Worked	(2) Worked	(3) # Hours Worked by Workers	(4) # Workers
Blackout * Whole Network Blackout	-1.01***	-0.06**	-1.14	-0.11
	(0.33)	(0.03)	(0.70)	(0.08)
Blackout * Network Without Blackout	-0.40***	-0.03***	0.33	0.03
	(0.11)	(0.01)	(0.24)	(0.03)
# Network Members	0.04***	0.00***	0.14**	0.01**
	(0.01)	(0.00)	(0.06)	(0.01)
Average Value of Outcome Variable	6.33	0.72	7.2	0.77
Observations	14,136	14,136	14,136	14,136
R-squared	0.343	0.362	0.080	0.081

Note: Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1

Table 19: **Spillover Weekly Effects of Blackouts**

VARIABLES	(1) Weekly Orders (Completed)	(2) Weekly Revenues (GhC)	(3) Weekly Expenses (GhC)	(4) Weekly Profits (GhC)
# Blackout Days With Whole Network Blackout	-1.49***	-14.29***	-2.20	-12.09**
	(0.29)	(3.84)	(2.48)	(5.07)
# Blackout Days Without Network Blackout	-0.41***	-5.15***	-1.68**	-3.47**
	(0.15)	(1.69)	(0.61)	(1.50)
# Network Members	0.14***	1.28***	0.92***	0.36
	(0.03)	(0.21)	(0.32)	(0.51)
# Days Responding	0.54*	5.07*	-0.42	5.48**
	(0.31)	(2.88)	(1.68)	(2.35)
Average Value of Outcome Variable	7.6	62.89	30.77	32.12
Observations	2,107	2,107	2,107	2,107
R-squared	0.123	0.161	0.109	0.094

Note: Standard errors are clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1