Baseline Report: Millennium Challenge Corporation Line Bifurcation Evaluation

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DD	Difference-in-Differences
ECG	Electricity Company of Ghana
EE	Energy Efficiency
EFOT	ECG Financial and Operational Turnaround
ERR	Economic Rate of Return
GDP	Gross Domestic Product
GHS	Ghanaian Cedi
GoG	Government of Ghana
GSS	Ghana Statistical Service
kWh	Kilowatt Hour
LB	Line Bifurcation
LV	Low Voltage
M&E	Monitoring and Evaluation
MCC	Millennium Challenge Corporation
PMC	Project Management Consultant
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
USD	United States Dollar

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Introduction

Poor electricity reliability constrains the well-being of businesses and households in many countries, and is a major concern in Ghana. Between 2012 and 2015, persistent power failures gave rise to the term “Dumsor,” meaning “lights off-on” in the local Akan language. According to the 2013 World Bank Enterprise Survey, 61.2% of firms in Ghana saw electricity reliability as a major constraint, with firms reporting an average of over 700 hours of outages annually, compared to 1.5 hours for firms in the U.S. Frequent outages continue to be a problem across urban areas of Ghana.

In August 2014, the Millennium Challenge Corporation (MCC) signed the Ghana Power Compact (“the Compact”), now worth 316 million USD, with the Government of Ghana (GOG). The Compact is designed to support the GoG’s goal of increasing electricity access and reliability while attracting private-sector investment. The Compact includes 4 main projects, including the ECG Financial and Operational Turnaround (EFOT) Project which aims to improve the quality and reliability of electricity through reduced outages and cost-effective service delivery by the Electricity Company of Ghana (ECG). The Technical Loss Reduction Activity within the EFOT Project includes an intervention to implement low voltage (LV) line bifurcation (LB) and network improvements in Accra, Ghana to reduce LV circuit lengths and ensure length does not impact quality of service or exceed a technical loss threshold. The LB intervention involves injecting new transformers in the LV network, “bifurcating” existing LV lines.

According to the program logic for the LB intervention, the expected **output** of the LB intervention is to reduce the length of LV circuits–the distance between transformers–to improve the quality of service. The targeted immediate **short-term outcome** of the LB intervention is to improve power reliability and quality. The theorized **long-term outcomes** from the intervention include improved economic outcomes for customers, realized by reduced spending on dealing with poor reliability and on alternative energy sources, increased electricity consumption, improved usage of electric appliances, reduced work disruptions, reduced electricity-related hazards, and increased revenues and profits for businesses.

MCC partnered with the GridWatch team to design and implement an impact evaluation of the LB investments in selected districts within Accra. This report presents findings from a baseline round of data collection for the evaluation.

Evaluation type, questions, and methodology

The LB impact evaluation uses a Difference-in-Differences (DD) design, informed by the site selection criteria for the new line bifurcation infrastructure in Accra, Ghana. Line bifurcation injections target settings where 1) the distance between a transformer and a grid endpoint is approximately 200-450 meters, or 2) the load factor on any transformer exceeds 70%. Based on these criteria, the Compact’s Project Management Consultant selected 76 sites for LB injections (the intervention’s “treatment”) in three electricity districts of Accra West: Achimota, Dansoman, and Kaneshie. Using the same criteria, the GridWatch team quasi-randomly selected a set of 75 control sites in the same districts to serve as a counterfactual for the treatment sites affected by the LB intervention.

The evaluation relies on two primary data sources. First, GridWatch monitoring devices have been deployed in LB treatment and control areas since June 2018 to monitor detailed trends in outages and voltage quality at the site level.. Second, the GridWatch team surveyed 1,000 households and 1,000 businesses across LB treatment and control sites, and will survey the same participants again as part of the endline survey. The surveys collect detailed data on customers' energy usage, including electricity spending, appliance ownership and usage, ownership and usage of electricity protection devices and generators, use of alternative energy sources, and impacts of reliability issues. Household data also include socioeconomic characteristics while business data include information on business activities, revenues, and profits. The survey data are used to confirm balance at baseline and to evaluate impacts on long-term socioeconomic outcomes.

The GridWatch data collected thus far provide important insights on the grid even in the absence of the LB intervention. SAIDI is estimated to be approximately 150, 149, and 115 hours per year in Achimota, Dansoman and Kaneshie, respectively. On average, devices report poor voltage quality approximately 20% of the time, defined as voltage outside 10% above or below Ghana's nominal voltage of 230 (thus, outside the range 207 to 253).

Baseline surveys were conducted between March and April 2021. Administrative data provided by the Project Management Consultant (PMC) and GridWatch monitoring visits verified that the LB construction activities were completed around March 2021. Endline surveys are planned for July to September 2022, giving an exposure period of 12-15 months for the impacts of the intervention to be realized. Impacts of the LB intervention will be estimated by comparing changes in outcomes from the period before the intervention to the end of the exposure period between treatment and control sites.

The household survey sample appears to be broadly representative of the urban population of Accra based on analysis of secondary household survey data, with the exception of an under-representation of higher-income households, resulting from the fact that high-income areas of Accra were not targeted for LB. The business survey sample targeted small and medium-sized businesses with 30 or fewer employees and consists mainly of very small businesses with just one or two employees due to LB sites mostly targeting mixed residential and business areas without large businesses. Median profits in the last month are GHS 400 (~USD 55) on revenues of GHS 1,200 (~USD 170).

A key aim of the GridWatch data and the baseline surveys is to confirm that control and treatment sites were similar at baseline. Balance tests using GridWatch data on reliability and voltage confirm that treatment and control sites experienced similar levels and trends in reliability and voltage quality in the months leading up to the launch of the LB intervention. Balance tests using survey data on energy use, location characteristics, and household and business characteristics indicate that samples in treatment and control sites are very similar at baseline. Any differences between treatment and control sites observed in the endline surveys can therefore be attributed to the LB treatment, rather than other differences between the sites. This confirms the internal validity of the DD research design.

Findings

The baseline findings are organized under a series of evaluation questions.

Q1. What is the impact of the infrastructure investments of the ECG Project on the reliability of power in areas of Accra targeted by the line bifurcation and network upgrades? Did the infrastructure improvements result in increased power available to

customers, reduce the frequency and duration of outages, and improved voltage stability?

GridWatch devices deployed across treatment and control sites since June 2018 allow us to evaluate trends in electricity reliability over time by site line bifurcation treatment status. Measures of reliability—mean daily outage minutes and the share of devices reporting bad voltage—exhibit seasonal fluctuations, but follow nearly identical trends in treatment and control sites prior to line bifurcation construction work. Formal statistical tests find no differences between treatment and control sites in either measure, confirming the internal validity of the DD design. Changes in reliability by treatment status at the end of the exposure period could thus reasonably be attributed to line bifurcation improvements. Data for April-August 2021, post-construction, provide suggestive evidence that LB infrastructure improvements are having the intended impact of improving electricity reliability, in terms of voltage quality. The endline report will present a longer time series of GridWatch data and formal tests of changes in measured power reliability over the full post-construction exposure period.

The survey data includes information on customers' electricity reliability experiences—count of outages, average outage duration, and average daily hours of bad voltage—over the past 30 days. As with the GridWatch data, we find no significant differences in measures of electricity reliability between treatment and control sites. Respondents in treatment sites had not perceived any improvements in power reliability relative to those in control sites at the time of the baseline survey. The endline report will test whether reported reliability measures differ significantly by treatment status after treatment exposure.

Q2. What are the economic and socio-economic benefits of access to reliable power on customers, including households and enterprises? How are these benefits distributed?

This question considers a broad set of long-term economic outcomes of the line bifurcation improvement activities and is therefore the core of the impact evaluation. We present baseline findings related to business and household energy usage and to household-specific outcomes, and hypothesize what benefits might be realized under improved reliability and voltage quality as a result of the LB intervention. We discuss other socioeconomic outcomes, related to appliance ownership and business outcomes, under more specific evaluation questions.

Energy Usage:

1. Mean monthly electricity spending for businesses is around USD 20 per month, compared to USD 6 for all other energy sources. Households spend an average of USD 16 per month on electricity and USD 10 for all other energy sources.
2. Most businesses report not using any other fuels for energy in the past 3 months. 21% used gas and 16% used charcoal, primarily among businesses in food and beverage-related activities. Use of other fuels is more common for households: 81% use gas and 65% use charcoal. Use is primarily tied to cooking where these are the primary energy sources for nearly all households.
3. Twenty percent of businesses and 30% of households own devices to protect against electricity reliability issues, such as stabilizers and fridge guards. Twenty-four percent of businesses and 29% of households report appliances being damaged due to voltage fluctuations in the past 12 months, costing an average of USD 33 and USD 47, respectively, to repair or replace.

As a result of the LB intervention, we expect electricity spending to increase in treatment site households and businesses relative to those in control sites, due to increased hours of electricity availability and higher quality electricity. Total spending on alternative energy sources may decrease, except for cases where the main alternative energy source is gas or charcoal for cooking. Damages to appliances due to voltage fluctuations and associated spending are hypothesized to fall due to LB treatment.

Household Outcomes

1. Only 6.7% of households use electricity for cooking. Households primarily report not using electricity to cook because other fuels are cheaper (67% of households), suggesting improved electricity reliability will not affect use of cooking fuels.
2. Households report using light bulbs for 8.3 hours per day, compared to 1.7 hours for all other sources of light. Households use light to read or study for an average of 1.2 hours per day, with 91% of these studying hours using lightbulbs.

For households, we expect no effect of LB treatment on the use of electricity for cooking as the primary barrier is cost rather than reliability, while the share of light provided by lightbulbs may increase if poor reliability is a reason for use of alternative light sources.

Q3. What happens within households and businesses when the power goes out? When it comes back on?

This section describes initial findings in three broad categories: (i) Alternative energy usage, (ii) Impacts of poor reliability, and (iii) Willingness to pay for improved reliability.

Alternative Energy Usage

1. Only 5.2% of businesses and 2.6% of households have a generator. Costs may be a barrier to investment in generators: the median customer spent 1.5 years' worth of electricity spending to acquire their generator.
2. Generators are not used frequently, with 77% of owners not using theirs in the past 3 months. Most customers with a generator use it only a few times per year. The decision to turn on a generator during an outage involves many factors. Use is generally reserved for situations with greater need for electricity. Costs of operating a generator are a concern.
3. Most households (88%) and businesses (89%) report that lightbulbs were their primary source of light over the prior three months. Cell phones (50%) and flashlights (25%) are the most common backup to lightbulbs during power outages. Surprisingly, 24% of businesses and 9% of households usually use no backup sources of lighting during outages, perhaps because these occur during the day.

To the extent that LB construction improves electricity reliability, we would expect generator use and associated costs to fall in treatment sites relative to control sites, although given the already low rates of generator usage this decrease may be small.

Impacts of Poor Reliability

1. Most businesses report that electricity is a very important obstacle to business activities, despite most of them being small with few electric appliances.
2. Some businesses can switch tools (from electric to manual) or business activities in response to outages, but stopping work is the most common temporary response to power outages.
3. Over one-quarter of businesses stopped business activities in the past month due to unreliable electricity, and the median business estimates that revenues in the past month would have been 16% (USD 31) higher if they had perfectly reliable electricity.

4. Households use electricity in a variety of ways, making it challenging to measure how unreliable electricity affects them outside of their energy use and spending. Loss of perishable food is one important challenge, reported by 27% households. Electricity outages do not appear to create difficulties for cooking, as electricity is not a primary cooking fuel for most households.

We expect business productivity and household electricity usage to improve and the prevalence of these adverse impacts of poor reliability to fall in treatment sites relative to control sites as a result of the LB intervention.

Willingness to Pay for Improved Reliability

1. We elicit respondents' willingness to pay (WTP) for different scenarios of improved electricity reliability and for a generator. The median respondent is willing to pay an extra tariff of around 15% of their monthly electricity spending to ensure perfect reliability, though some respondents indicate being willing to pay much more. Around one-third of households and businesses are not willing to pay anything more for perfectly reliable electricity. Households and businesses are willing to pay more to avoid outages than voltage fluctuations.
2. Businesses would pay more to avoid a long unannounced outage than a long announced outage, and prefer 4 shorter outages to one longer outage with the same total duration. Household willingness to pay does not differ across these scenarios.
3. Median WTP for a generator is USD 137 for households and USD 198 for businesses, with 10% of each not being willing to pay anything for a generator.

To the extent that LB construction improves electricity reliability, WTP for reliable electricity and for a generator should fall in treatment sites relative to control sites.

Q4. How long does it take households and businesses to make lumpy investments in power-consuming technology when the reliability of the grid improves?

1. Households typically own 4 or 5 different types of electric appliances. The most common are mobile phones (99%), fans (94%), televisions (90%), electric irons (79%), and refrigerators/freezers (74%).
2. Businesses typically own 3 different types of appliances. The most common are again mobile phones (99%), fans (75%), televisions (52%), and refrigerators/freezers (49%), potentially reflecting the small nature of most sample businesses. Just 9% of businesses report having any non-electric machines for business purposes, the most common of which are manual (i.e., foot pedal-operated) sewing machines.
3. Around half of respondents (40% of households and 50% of businesses) have no plans to purchase an additional appliance, either currently or in a hypothetical scenario with perfectly reliable electricity. When probed, the most common appliances households and businesses would purchase are refrigerators/freezers and televisions.

Households and businesses may invest more in power-consuming technology as electricity reliability improves and their ability to benefit from such investments increases, if they believe that the reliability improvements are large and likely to last. Such changes may not be detectable by the end of the exposure period for the line bifurcation construction treatment, but questions about appliance ownership and purchase plans can provide insight into consumer perceptions of reliability and awareness of any improvements.

Q5. What is the program's overall impact on the profitability and productivity of enterprises? What are the mechanisms or channels through which these impacts occur?

The median business in the sample has estimated revenues of USD 183 costs and reported profits of USD 61 over the past month. Profits are higher on average for businesses engaged in retail, with more employees, and with a larger share of male employees.

Improved electricity reliability could affect business profits in two main ways. First, more reliable electricity could cause businesses to reduce their use of alternative energy sources in favor of more electricity use, which would reduce business costs if electricity is less costly than its alternatives or back-ups. Second, improved reliability could increase business revenues and profits by reducing interruptions to business or by increasing use of productive electric appliances.

Q6. To what extent do small and medium firms (up to 30 employees) respond to more reliable, accessible, and/or higher quality power by expanding or intensifying production, expanding employment, or investing in expanded plant or other fixed assets and/or different production technologies reliant on electricity?

Businesses that perceive that electricity is more reliable could respond in a variety of ways. Assuming reliability improves productivity, this could motivate increases in employment. But most businesses in the sample are owner-operated with just 1 or 2 employees so may be unlikely to change use of labor. Most businesses employ only women, and most employees are engaged full-time.

Businesses are typically open for 12 hours per day, from 8am to 8pm. The potential effect of improved electricity reliability on business hours is ambiguous. Businesses might work longer hours if these hours are more productive and profits increase, or they might work fewer hours if they can reach target output or revenue levels in a shorter amount of time. Businesses might also be more likely to stay open at night with more reliable electric lighting.

Businesses might invest in more electric appliances as they could use these more reliably, and substitute away from presumably less efficient non-electric alternatives. Businesses own between 6 and 7 electric appliances from three different appliance types, on average. In addition to a mobile phone and often a television and/or refrigerator, businesses typically own several appliances of a particular type associated with their business activity. Around 15% of businesses own electric sewing machines, and nearly two-thirds of these own two or more. These businesses operate their sewing machines for 11 hours per day, and are more likely to have non-electric sewing machines as backups. Businesses engaged in clothing production or repair might therefore benefit more from improved electricity reliability.

Q7. Are customers notified ahead of schedule of their outages? What is the differential impact on customers between known and unknown outages? What is the impact of known versus unknown outages on customer relations?

Outages caused by load shedding and maintenance operations are often planned and announced in advance. As planned outages are not expected to vary as a result of LB construction, treatment should not affect awareness of or attentiveness to planned outages. This question is therefore separate from the evaluation of the LB construction activities, but may still be of interest to the same stakeholders.

Most customers (87%) report not being aware of any outages ahead of time in the past year. This could be due to poor dissemination of planned outages by ECG, low attention to this information by customers, and/or a large share of outages being unplanned. Most customers that do report ever being notified about outages in advance find out the same day (53%) or the day before (38%). Neighbors are the main source of information (67% of respondents), indicating that advance notice of outages usually spreads by word of mouth. Around one-third of respondents find out about outages on the radio.

Over half of respondents have a negative attitude toward current electricity quality, reporting that they believe Dumsor may continue to be a problem today. Being aware of more outages in advance is not associated with different attitudes about electricity.

Assessment of Program Logic Risks

Electricity reliability trended similarly prior to the LB intervention in treatment and control sites and household and business survey respondents are similar on observable characteristics. This indicates that the Difference-in-Differences evaluation strategy should successfully identify impacts of the LB intervention on electricity reliability in the short-term and on household and business socioeconomic outcomes in the long-term as measured during the planned endline surveys.

LB construction appears to have been implemented according to plan. A potential risk to the evaluation is if LB improvements do not significantly improve electricity reliability for customers. Initial data post-construction from GridWatch devices are encouraging in this regard but it is too soon to tell whether these reliability improvements are spurious or persistent.

A benefit of the evaluation design is that customers do not need to perceive any reliability improvements to experience long-term benefits. Electricity consumption may increase simply because electricity is available for more hours per day, while business revenues may increase by being able to operate appliances more consistently with fewer disruptions. Awareness of the improvement is not required in either case. However, larger changes in energy use, electricity consumption, and business and household outcomes are more likely to be observed if customers perceive improvements in electricity reliability. The endline surveys will investigate respondent awareness of any reliability changes.

Baseline data on coping mechanisms suggests potentially large benefits from any reduction in outages. Few households or businesses have generators or other alternatives to electricity, and many businesses stop their activities in response to outages. LB improvements could therefore lead to significant increases in electricity consumption and appliance use even if use of alternative energy sources does not fall. Businesses in particular could benefit from fewer work disruptions, particularly for businesses whose activities are more reliant on electric appliances, such as sewing shops with electric sewing machines or cold stores with refrigerators. These businesses could see increased revenues and profits. Savings from the costs of repairing or replacing appliances damaged by voltage fluctuations may also be significant.

1. Introduction

In urban areas of Ghana, more than 90% of households are already connected to the electric grid. In these settings, a primary issue is the reliability of the grid rather than the lack of access to electricity. Between 2012 and 2015, persistent power failures in Ghana negatively affected its economy and gave rise to the term “Dumsor,” meaning “lights off-on” in the local Akan language. According to the 2013 World Bank Enterprise Survey, 61.2% of firms in Ghana saw electricity reliability as a major constraint, with firms reporting an average of over 700 hours of outages annually, compared to 1.5 hours for firms in the U.S.

Anecdotally, we know that frequent outages constrain the economic well-being of households and small businesses by reducing the benefits from, and discouraging investments in, welfare-improving appliances (like fans, refrigerators, or income-generating assets like sewing machines). To mitigate the impacts of these outages, customers make large investments in substitutes for high quality grid electricity. Investments in backup generators and stabilizers potentially crowd out productive investments. Yet the scope of the grid unreliability problem is not well understood. Governments and utilities are forced to make important operational and investment decisions without accurate information on the frequency, duration, and geographic extent of power outages, the extent to which blackouts and brownouts affect households and businesses (and, indirectly, the local economy), or the most cost-effective ways to improve grid reliability.

On August 5, 2014, the Millennium Challenge Corporation (MCC) signed a compact with the Government of Ghana (GOG) now worth 316 million USD.[1] The Ghana Power Compact (“the Compact”) supports the Government of Ghana’s goal of increasing electricity access and reliability while attracting private-sector investment. It entered into force in September 2016 and is scheduled to be completed by June 2022.

The Compact currently includes four projects:

1. ECG Financial and Operational Turnaround (EFOT) Project,
2. Regulatory Strengthening and Capacity Building Project,
3. Access Project, and
4. Energy Efficiency and Demand Side Management Project.

In particular, the ECG Financial and Operational Turnaround Project’s objectives are to improve the quality and reliability of electricity through reduced outages and cost-effective service delivery by ECG, reduce aggregate technical, commercial and collections losses, and to ensure ECG can serve as a creditworthy and credible off-taker under power purchase agreements. The Compact aims to achieve these objectives by reducing implicit subsidies (created by losses, underpricing, and under-billing) and ensuring cost-recovery and reinvestment in the distribution sub-sector through introduction of Private Sector Participation (PSP) in the governance and management of ECG, and through infrastructure and foundational investments designed to reduce losses and improve service quality.

There are five main activities under the EFOT project:

1. Private Sector Participation (PSP) Activity,
2. Modernizing Utility Operations Activity,
3. Reduction in Commercial Losses and Improvement of Revenue Collection Rates Activity,

[1] The Ghana Power Compact was originally worth $535.6 million, with the Governments of the United States of America and Ghana contributing US$498,200,000 and US$37,365,000 respectively. The compact was reduced by $190 million in October 2019 in response to the Government of Ghana's decision to terminate the concession agreement between the Electric Company of Ghana Ltd (ECG) to private operator Power Distribution Services Ghana Ltd (PDS)—a necessary condition as part of the compact. In addition to the removal of $190 million (which reduced compact funding to $308 million), in 2021 the MCC board approved an extension of the compact end date to June 2022 due to delays in implementation resulting from the COVID-19 pandemic. The request added approximately 8 million USD to cover costs associated with the timeline extension.

4. Technical Loss Reduction Activity, and
5. Outage Reduction Activity

The activity of interest for the GridWatch team is the Technical Loss Reduction Activity. The aim of the activity is to lower thermal losses for primary and secondary distribution systems in the ECG Target Regions. The interventions under this activity include

1. Updating distribution design and construction standards to comply with international best practices for low loss and economical design,
2. Implementing low voltage (LV) bifurcation and network improvements to reduce low voltage circuit lengths and ensure length does not impact quality of service or exceed a technical loss threshold,
3. Installing 2 bulk supply points (BSPs) with feeders to ease overloading and avoid brownouts from existing primary substation,
4. Installing 2 primary substations with interconnecting sub-transmission links and medium voltage offloading circuits to help reduce technical losses and avoid extended outages caused by failures or by reaching maximum capacity at geographically adjacent substation, and
5. Introducing reactive power compensation for primary substations to optimize power levels at 33/11 kV substations.

MCC contracted the GridWatch team to design and implement an impact evaluation of targeted investments in low-voltage (LV) line bifurcation (LB), sub-Activity 2 under the Technical Loss Reduction Activity. The Line Bifurcation intervention initially targeted three electricity districts in Accra West: Achimota, Dansoman and Kaneshie. The intervention was later extended to the Mampong and Legon districts, but the GridWatch evaluation focuses on LB improvements in the initial three districts, where LB construction took place from around November 2020 to March 2021[2].

At a high level, the GridWatch team's aim is to measure how primary Compact outcomes, including the frequency (SAIFI) and duration (SAIDI) of outages[3] and voltage level irregularities, change in response to this intervention, and to evaluate the socioeconomic impacts for households and businesses of improvements in those outcomes due to the Compact.

The research team and MCC developed a set of evaluation questions and outcomes of interest, and the research team, in close collaboration with MiDA, MCC, ECG and other compact stakeholders, has refined these questions and developed an approach to answer them. This report outlines the initial results from the baseline stage of the approved evaluation design. We employ a quasi-experimental research design using the criteria for the selection of location for LB intervention investments under the Compact to identify comparable control areas, and apply a difference-in-differences analysis to compare changes in electricity quality and in socioeconomic outcomes over time across these areas.[4]

To measure changes in electricity quality and reliability with a higher degree of granularity and precision than is otherwise available, we deployed the GridWatch suite of technologies[5] in both the areas targeted

[2] Construction activities initially began in January 2020 but did not progress very much before being put on hold due to the onset of the COVID-19 pandemic.

[3] Specifically, for a given service area and a given time frame SAIFI measures the number of electricity outages experienced per customer and SAIDI measures the total duration of electricity outages per customer.

[4] A complementary approach to analyzing the impacts of differences in electricity quality uses differences in electricity outages during the Dumsor electricity crisis in Ghana from 2012-2016. We collected data for this "Dumsor Priority Feeder" approach in tandem to the data collection for the main "Compact Quasi-Experimental" approach. The Dumsor Priority Feeder approach takes advantage of the fact that ordinary households and small businesses may happen to be connected to a feeder that serves a priority customer while a statistically equivalent (in terms of observed characteristics) group of neighboring households and small businesses are not. Results are included in Annex A to this report.

[5] The GridWatch suite is designed to detect all types of outages, including those originating in the low-voltage, medium-voltage, and high-voltage systems. Using spatial and temporal analytical tools, the technology is able to detect when a large number of devices in a particular area experience an outage at the same time, for example if these are all connected to the

for the LB intervention and in control areas to measure outage duration, outage frequency, and voltage quality and to determine outage location on the low-voltage distribution level of the electrical grid at households and firms in Accra, Ghana. This data collection began in June 2018 and will continue through the end of the evaluation. Surveys in March-May 2021 collected data on household and business outcomes in both the LB intervention areas and control areas. At the end of the LB intervention exposure period of just over one year in July-September 2022, we will conduct a round of endline surveys targeting the same households and businesses surveyed at baseline. These two rounds of surveys, before and after the LB interventions are implemented, enables a difference-in-differences strategy.

The remainder of this introduction discusses the program logic (theory of change) for the LB intervention, assumptions about the economic rate of return (ERR) and benefits of the intervention, and the contribution to the literature and policy relevance of this evaluation. We list the evaluation questions and provide more detail on the evaluation methodology and data in Section 2 of this report. Section 3, the bulk of the report, summarizes findings from the baseline round of data collection, which took place before LB intervention investments were completed, for each evaluation question. Section 4 discusses potential risks to the program logic and evaluation strategy.

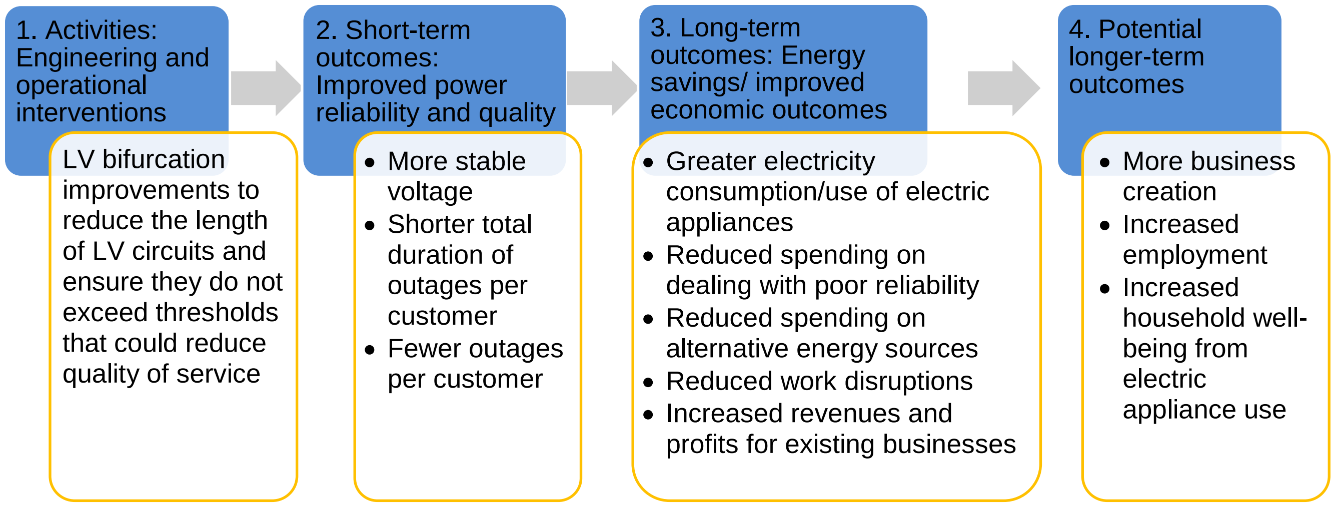
1.1 Program Logic

The Low Voltage (LV) Line Bifurcation (LB) and network improvements intervention of the Technical Loss Reduction Activity under the Ghana Power Compact's EFOT project is the focus of this evaluation. The program logic, or theory of change, for the LB intervention, is summarized in Figure 1.

The LB intervention involves injecting new transformers in the LV network. These new transformers "bifurcate" existing LV lines, reducing the length of existing LV circuits—the distance between transformers on the network. Longer LV circuits create greater risk of loss of voltage and may also lead to excess electricity load on the LV lines, beyond what the transformer can sustainably provide. The **output** of the LB improvements intervention is to reduce the length of LV circuits to ensure they do not exceed thresholds that could reduce the quality of service. The location of the LB improvements are targeted at locations in Accra where the endpoint of the LV grid is above 500 meters from the nearest transformer and the load factor on the transformer exceeds 70%. These parts of the grid are therefore those that could most benefit from a line bifurcation transformer injection.

same infrastructure. The technology can thereby distinguish between an LV outage and an MV or HV outage with a high degree of confidence.

Figure 1. Program Logic for Compact Line Bifurcation Intervention



The immediate **short-term outcome** of the LB intervention (and other interventions under the Technical Loss Reduction Activity) is to improve power reliability and quality along three dimensions: voltage stability, frequency of outages (SAIFI), and duration of outages (SAIDI). The expectation is that areas receiving LB investments will have more stable voltage levels, fewer power interruptions, and shorter total durations of outages after the interventions have taken place. We will measure these outcomes at the site level using the GridWatch technology.

We expect that the LB intervention will be most likely to improve voltage quality, as this aspect of power quality is directly related to the length of LV circuits and the local electricity load factor, which are addressed by the LB intervention outputs. The LB intervention should also reduce frequency and duration of outages to the extent that outages are caused by issues in the local LV network. But outages may occur for a variety of reasons, including issues at higher levels of the grid, such as load shedding at the MV or HV feeder level. The GridWatch data can determine what fraction of power outages and power outage duration is caused by failures in the LV network or failures at the feeder level. If feeder-level electricity interruptions make up a large share of all customer-level electricity interruptions, reductions in outage frequency and duration due to the LB intervention may be limited.

We consider two main categories within the set of **long-term outcomes** of changes in electricity reliability following line bifurcation improvements, Stage 3 of the program logic. The first relates to improvements in energy usage, and the second to improvements in business outcomes. Customers use electricity to power a variety of electric appliances, which provide services and utility. For customers to benefit from improved power reliability, we would therefore first expect to see improvements in energy usage. By "improved" energy usage, we mean increased electricity spending arising from increased usage of electricity, shifts toward consumption of electricity rather than alternative fuels (presumed to be less desirable in general) and less spending on mechanisms to protect against unreliable power or to deal with its consequences. This could involve operating electric appliances for more hours, purchasing better quality equipment, and spending less money on replacements for reliable grid power, such as backup generators and generator fuel, voltage stabilizers, or alternative fuels.

Part of the improvement in energy usage may not require any awareness by customers that power quality has improved. More hours of electricity per day may increase electricity consumption mechanically without any active customer decision. To the extent that they use alternative energy sources (generators, gas, charcoal, etc.) as a substitute for electricity, this would also mechanically reduce their use of and spending on these alternatives. Other improvements in electricity usage, such as increasing their ownership of electric appliances or reducing ownership of generators or devices to protect against poor reliability, would require customers to both observe that power quality has improved and believe that the improvements are likely to persist. Such changes are unlikely over the short exposure period considered in this evaluation. Customers may need more time to be convinced reliability gains will be persistent before investing in more appliances, and are likely to store any generators and protective devices in the event of a possible future Dumsor period rather than discard this equipment.

Businesses could benefit directly from improved power reliability following LB interventions in two main ways. First, businesses that use electricity for their operations could experience fewer work disruptions. This will allow them to spend more of their working hours producing goods and services. This could increase revenues for example by generating gains in efficiency or customer activity with more reliable power. To the extent that improved energy usage reduces costs for businesses, or increases them by less than their revenues increase, profits could also increase. These benefits will be largest for businesses that rely most on electricity for their operations, and smallest for those where electricity use is tangential to their activities.

In addition to these long-term outcomes, which we expect to be able to observe during the project exposure period of just over one year, we also consider several **potential longer-term outcomes**. These may result from the long-term outcomes of the LB interventions but are unlikely to be observed by the time we conduct our endline surveys between July and September 2022. To the extent that business profits increase, entry of new businesses could increase in LB intervention areas. Even absent any business creation employment could increase in LB intervention areas if existing firms increase the scale of their operations. Finally, household well-being could increase from increases in electric appliance use in a variety of ways. Household members could gain more utility from their leisure time through use of electric appliances, may increase their productivity if working from home or even searching for work from home, may reduce their risk of health issues due to switcher to cleaner energy sources, and may experience improved educational outcomes from better studying conditions. As we do not expect to observe such changes in the timeline for this evaluation, we do not focus on these outcomes, but report on related variables to provide context for potential future work.

1.2 ERR and Beneficiary Analysis

MCC's Economic Rate of Return (ERR) analysis applies several methodologies to estimate likely Compact impacts, which are expected to be roughly 3-4% of Ghana's GDP. The analysis focused on the economic costs of power outages by quantifying their impacts on productive activities. For example, MCC analysts developed a fixed-price multiplier from an existing Social Accounting Matrix (SAM) and then applied the multiplier to estimates of the increases in electricity likely to be generated by the compact. MCC also developed estimates of the cost of outages in terms of dollars per kilowatt-hour for firms by estimating reductions in value added due to the costs of operating a backup generator and losses of value added due to the temporary cessation of economic activity. They then multiplied these estimates by the expected increase in kilowatt-hour production generated by compact investments.

The ERR notes that "the primary beneficiaries of the EFOT Project are consumers of electricity engaged in productive activity in the ECG Target Regions. These regions generate over 22 percent of the gross domestic product (GDP) of Ghana and represent more than 23 percent of ECG's total customers. The proposed interventions are expected to reduce losses in added value in terms of lost income to the owners of businesses (or owner-operators as the case may be for informal activities) and wages because of service disruptions."

The impact evaluation complements the ERR estimates, estimating direct impacts of outages on sales and profitability, and investigating the mechanisms through which reduced outages lead to these changes by measuring the impacts on firms' decisions to invest in electricity-using assets or to reduce investments in substitutes for grid electricity, such as generators.

We note several points of departure from the analysis in the ERR. First, while the ERR focused on outages, we intend to measure the impacts of voltage fluctuations as well. Low or fluctuating voltage can lead to economic losses by damaging electrical appliances, and the fear of voltage issues can prevent firms or households from investing in productivity- or welfare-enhancing equipment. To consider a simple example, a seamstress may opt to use a manual-powered sewing machine if they fear that voltage issues would damage an electric machine. With an electric machine, however, the seamstress might be able to increase productivity. Because the GridWatch technologies can measure the voltage quality and frequency experienced by the customer, we will be able to measure the impacts of improved voltage in addition to improved reliability. Improved voltage quality is likely to be a primary short-term outcome of the Compact LB interventions this evaluation focuses on.

As a second point of departure, the ERR focuses on short-run losses at existing firms. The endline will measure the impact of the LB intervention on the number of new businesses created. For example, if all firms in a certain industry require a generator to maintain productivity, this essentially serves as a tax to being in business, which, on the margin, will reduce new business creation.

Third, we will also measure household impacts. Anecdotally, households often spend significant amounts of money on electrical equipment to protect household appliances against surges and voltage fluctuations. Households may also experience welfare reductions from power outages, for example through the expiration of foods or medications that require refrigeration.

Finally, the ERR estimates that SAIDI in the three LB intervention districts is approximately 50 hours per year. An analysis of the GridWatch data collected thus far puts SAIDI significantly higher, at approximately 150, 149, and 115 hours per year in Achimota, Dansoman and Kaneshie, respectively. The ERR estimates SAIDI could be driven down by approximately 50%, or 25 hours per year. We perform statistical power calculations using the mean and standard deviation observed in the GridWatch data collected so far. These calculations use district-by-month data as these balance accuracy and statistical noise. The Minimum Detectable Effect (MDE) is a 37% reduction in SAIDI relative to the baseline. Reassuringly, this is smaller than the 50% improvement that was estimated in the ERR. The MDE expressed in hours per year is 50, which is significantly higher than the 25 hours per year targeted in the ERR, however given the very different baseline SAIDI levels, this poses a minimal concern to our evaluation strategy.

1.3 Contribution to the Literature and Policy Relevance

There is a small literature on the effects of electricity reliability issues on socioeconomic outcomes. Allcott, Collard-Wexler, and O'Connell (2016) and Fisher-Vanden, Mansur, and Wang (2015) study firm responses to scheduled rolling blackouts in India and China, respectively, and find that the negative effect of outages on firm productivity is mitigated to some extent by a firm's ability to store inputs over time and reallocate production to non-outage hours.

In Ghana, two papers analyze impacts of the Dumsor electricity crisis on socioeconomic outcomes. Hardy and McCasland (2019) find that one additional blackout day among small firms is associated with an 11% decrease in weekly profits, even though firm owners respond to blackouts by shifting production to non-blackout days. Abeberese, Ackah, and Asuming (2017), in a policy brief commissioned by the International Growth Center (IGC), found that power outages during the 2012-2015 Dumsor crisis had a significant negative impact on productivity among small Ghanaian firms, and that one extra day of outages is associated with a 1% reduction in labor productivity and total factor productivity (TFP). Their analysis, however, relies on the assumption that all firms within a given city were equally likely to experience a power outage at any particular time. We are not aware of any additional rigorous quantitative evidence on the effect of the Dumsor crisis on socioeconomic outcomes in Ghana.

These two papers on Ghana's Dumsor crisis relied on the assumption that power outages were distributed randomly across firms and households. Any claim around causality relies on the assumption that firm blackouts are randomly assigned conditional on a time control, which is unlikely in this setting given anecdotal evidence that blackouts are often concentrated in areas with limited political or economic influence. It is up for debate whether this assumption would hold in the Ghanaian context, where power outages are largely at the discretion of ECG, either directly (through rolling blackouts) or indirectly (through differential investment in low voltage infrastructure). There is still no rigorous, causally identified estimate of the effect of improved reliability in Ghana on socioeconomic outcomes. Allcott, et al. (2016) and Fisher-Vanden, et al. (2015) both focus on short-run outcomes and are not able to address the possibility that, for example, persistent outages discourage new firms from entering a market in the first place. In addition, neither paper provides evidence on the effect of more frequent and longer duration outages, nor do they study unannounced electricity outages caused by infrastructure failures, which could have a higher impact than the effect they identified due to firms' inability to prepare for unannounced outages by storing inputs or shifting working hours. Due to these gaps in the literature, we believe that a rigorous, quantitative study on the effects of both unannounced low-voltage outages and high-frequency rolling blackouts in the Ghanaian context would be a meaningful contribution to the literature.

Over the next several decades, almost all of the increase in energy demand worldwide is expected to come from developing countries. In response to rapidly growing electricity demand in Sub-Saharan Africa, particularly in its cities, electricity companies in the region will be evaluating approaches to improve the reliability of their urban electricity networks. In addition, utilities, as well as international donor agencies, will want to know how to do so most effectively. However, there is limited information on both the effect of network investments on reliability and the effect of improved reliability on socioeconomic outcomes. At the conclusion of the endline stage, this impact evaluation intends to address both issues. It will be able to provide evidence on the effectiveness of transformer line bifurcation upgrades on reliability, and it will then provide both short-run and medium-run estimates of the effect of these reliability improvements on household well-being and business performance. With better estimates of these effects, public actors can make more informed decisions about which infrastructure investments may generate the largest economic returns.

2. Evaluation Design

The GridWatch team was tasked with conducting an impact evaluation of the line bifurcation investments made by MCC under the Technical Loss Reduction Activity. The evaluation design proposed by the GridWatch team relies on a quasi-experimental approach to accurately measure and attribute the socio-economic impact observed among households and businesses in Accra, to MCC's investments. The evaluation design was informed by the line bifurcation construction plan, which allowed the evaluation team to identify a similar control group of respondents to serve as a counterfactual against which to compare the treatment group affected by the LB intervention. The team also developed 7 core evaluation questions in collaboration with MCC, which explore the socio-economic impacts of the line bifurcation and network improvements.

2.1 Evaluation Questions

MCC and the GridWatch team agreed on a set of seven evaluation questions to explore within this low voltage line bifurcation and network improvements impact evaluation study. The number and order in which the questions appear here are the same in which they are referenced throughout the report.

1. What is the impact of the infrastructure investments of the ECG Project on the reliability of power in areas of Accra targeted by the line bifurcation and network upgrades? Did the infrastructure improvements result in increased power available to customers, reduce the frequency and duration of outages, and improved voltage stability?
2. What are the economic and socio-economic benefits of access to reliable power on customers, including households and enterprises? How are these benefits distributed?
3. What happens within households and businesses when the power goes out? When it comes back on?
4. How long does it take households and businesses to make lumpy investments in power consuming technology when the reliability of the grid improves?
5. What is the Program's overall impact on the profitability and productivity of enterprises? What are the mechanisms or channels through which these impacts occur?
6. To what extent do small and medium firms (up to 30 employees) respond to more reliable, accessible, and/or higher quality power by:
    a. Expanding or intensifying production
    b. Expanding employment
    c. Investing in expanded plant or other fixed assets and/or different production technologies reliant on electricity
7. Are customers notified ahead of schedule of their outages? What is the differential impact on customers between known and unknown outages? What is the impact of known versus unknown outages on customer relations?

The findings section explores the baseline results pertaining to each evaluation question in detail.

Table 1 details the list of outcome variables that are further discussed in the Findings section, specific to each evaluation question. The first column indicates the evaluation question and the second column lists the outcome variables discussed in this report. In some cases, we list a category of outcome variables which encompasses several specific variables. For example, under "Use of alternative fuels for energy in the past 3 months" for evaluation question 2, we report on the use of a variety of specific fuels. Where applicable, outcome variables are discussed separately for households and businesses in the findings section.

Evaluation question 2 is relatively broad, with significant overlap with several other evaluation questions. Any outcome variable that falls under a more specific evaluation question is listed in Table 1 and reported on in the Findings section under that question, rather than under evaluation question 2.

For variables relating to monetary amounts, we report results primarily in the local currency, Ghanaian Cedis (GHS), but also provide estimated values in US Dollars (USD) in the text discussion.

Table 1. Outcome Variables by Evaluation Question

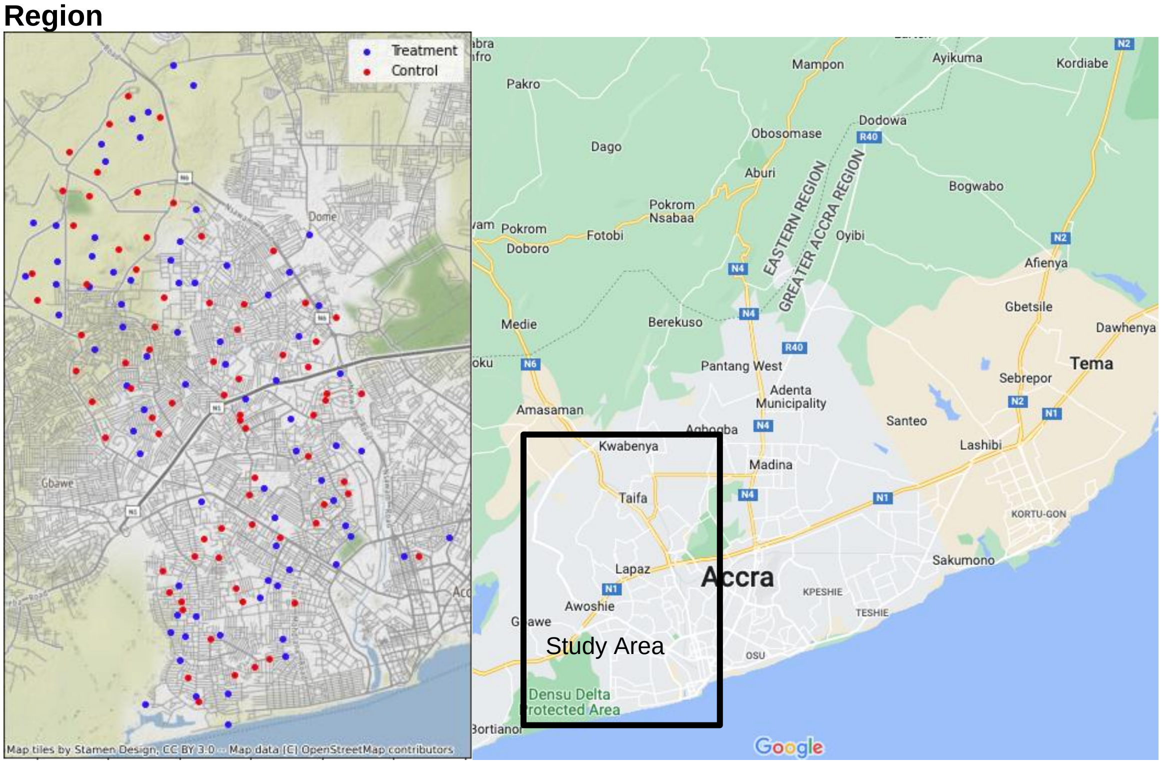
Evaluation Question	Outcome Variables
1. Power Reliability	Count of outages in past 30 days
	Average outage duration in past 30 days
	Total outage duration in past 30 days
	Average bad voltage hours per day in past 30 days
2. Socioeconomic Benefits (General)	Monthly electricity spending
	Spending on alternative fuels in average month
	Ownership of alternative electricity sources (generators, in particular)
	Generator use
	Use of alternative fuels for energy in past 3 months
	Household use of electricity and other fuels for cooking
	Use of different sources of lighting
	Household use of lighting sources for studying
	Any electricity protective devices
	Types of protective devices owned
	Spending to deal with appliances damaged by poor reliability
3. Impacts of Poor Electricity Reliability	Generator use
	Backup sources of lighting
	Importance of electricity as an obstacle to business
	Business responses to poor reliability in the short- and long-term
	Days in past month stopped business due to reliability
	Percent of business hours in past month stopped due to reliability
	Estimated difference in business revenues with perfect reliability
	Household responses to poor reliability
	Primary reliability issues willing to pay to improve
	Willingness to pay for improved electricity reliability
	Willingness to pay for a generator
4. Investment in Electric Appliances	Ownership of different appliance types
	Count of and year of most recently acquired mobile phone, refrigerator/freezer, television, fan, and air conditioner
	Next electric appliance planning to purchase
	Electric appliances would purchase with perfect reliability
5. Business Profits and Productivity	Total revenue in past 30 days
	Total wages and benefits paid in past 30 days
	Total materials costs in past 30 days
	Total reported business costs in past 30 days
	Total reported profit in past 30 days
6. Business Responses to Improved Reliability	Number of female employees
	Number of male employees
	Usual daily business working hours
	Business open outside daylight hours
	Total number of electric appliances owned
	Daily hours of sewing machine use
	Total number of non-electric productive machines owned
7. Outage Awareness	Percent of outages in past year aware of in advance
	Timing and source of notification for planned outages
	Perspectives on Dumsor

In addition to these outcome variables, we also report on some additional characteristics of the businesses and households in our baseline survey in section 3.1.

2.2 Evaluation Methodology

The Compact Quasi-Experimental approach employs a Differences-in-Differences (DD) design. This choice of methodology was informed by the criteria for where to locate the new line bifurcation infrastructure in Accra, Ghana. The Project Management Consultant (PMC), in its role as engineering designer and construction supervisor under the EFOT project, determined that line bifurcation injections would target adding a transformer in settings where 1) the distance between a transformer and a grid endpoint exceeds 500 meters, OR 2) the load factor on any transformer exceeds 70%.[6] The list of LB injection site locations shared by the PMC revealed that these criteria were not strictly adhered to, however, and instead we determined that nearly all sites were located between 200 and 450 meters from the nearest transformer.

Figure 2. Treatment and Control Site Locations and Map of Study Area Relative to Greater Accra Region



Implementing a DD design requires identifying a control group to serve as a counterfactual against which to compare the treatment group affected by the LB intervention. For a rigorous impact evaluation, the control and treatment sites ought to be statistically identical prior to the intervention. We therefore quasi-randomly selected control service areas located 200-450m from any transformer but where no LB injection is planned. This mirrors the key selection criterion for line bifurcation site selection.[7] This procedure resulted in a sample of 76 line bifurcation injection (treatment) sites and 75 nearby control

[6] While the original evaluation design plan was to implement a Regression Discontinuity Design (RDD) approach using the 500m LV line distance from transformer criteria to establish the discontinuity in which locations would and would not receive an injection, we determined that since the PMC was not adhering strictly to this cut-off/threshold, we would not be able to accurately determine the causal effects of the Compact using an RDD approach. In particular, many treatment sites that are near to existing transformers were selected due to high load factors.

[7] Based on our conversations with the PMC, though other criteria were considered in choosing injection location, the main engineering guideline used by the firm was to identify parts of the grid over 200m from the nearest transformer.

areas, all of which are located a similar distance from the nearest transformer and can thus be expected to have similar characteristics at baseline prior to the LB intervention. There are 42 treatment and 41 control sites in Achimota, 19 treatment and 19 control sites in Dansoman, and 15 treatment and 15 control sites in Kaneshie.

Figure 2 shows a map of the treatment sites targeted for line bifurcation and comparable control sites as described above, alongside a map showing where the study area is located relative to the rest of the Greater Accra Region of Ghana. The three electricity districts initially selected for line bifurcation improvements are all located in Accra West. Study sites in these urban districts are primarily located in mixed residential/business areas rather than purely residential neighborhoods or business districts, meaning wealthier households and larger formal businesses will not be included in the evaluation. The fourth district selected for the LB intervention, Mampong, is located in a largely rural area outside of the Greater Accra Region and is visible at the top middle of the map on the right of Figure 2. LB construction began later in this site, and it is not included in this evaluation.

Using the DD approach, we will estimate the causal effect of improvements in power reliability and quality on socioeconomic outcomes. First, we estimate the extent to which LB injections affect power reliability and quality. Next, we analyze how LB injections affect firm and household energy consumption, business revenues, profits, and activities, the purchasing and usage patterns of electrical appliances or machinery, and other outcomes listed in Table 1. We will also examine specific mechanisms through which improved electricity reliability affects business productivity, profits, and revenues.

We implement the DD strategy by estimating the following regression equation:

$$Y_{ist} = \beta_0 + \beta_1 * \ BIFURCATION_s + \ \beta_2 * POST_t + \ \beta_3 * TREAT_{ist} + \sum \theta X_{ist} \ + \ \varepsilon_i \qquad (1)$$

In this equation, Y_{ist} represents outcomes for respondent *i* in site *s* at time *t*. $BIFURCATION_s$ is an indicator of whether the customer is in a site selected for bifurcation and $POST_t$ is an indicator for whether the customer is being observed after the line bifurcation work has been completed. Covariates X_{ist} control for site and respondent characteristics collected at baseline. The coefficient of interest is β_3, which measures the effect of treatment – being in a site selected for bifurcation after the bifurcation work has been completed ($TREAT_{ist} = BIFURCATION_s * POST_t$). This coefficient is the estimated causal impact of LV line bifurcation on the outcome.

To test for a “first stage”, we estimate the model above where the outcomes are monthly outage frequency, outage duration, and voltage fluctuations. This specification is run at the level of survey sites, as this is the level at which GridWatch measures electricity reliability. To test for reduced-form impacts, we estimate the model with socioeconomic outcomes described above. By combining this estimate with metrics of the first-stage impact of bifurcation on power reliability and quality, we will estimate the causal effect of power reliability or power quality on the outcome.

The DD strategy leverages the fact that customers in treatment areas will have their line bifurcated with a transformer injection, which could lead to higher power reliability and quality, while customers in otherwise similar control areas will not. The DD econometric identification assumption relies on two testable requirements. First, the control and treatment sites must satisfy the parallel trends assumption: control and treatment sites should have had similar trends in reliability over time prior to the line bifurcation. GridWatch outage and voltage quality data collected since 2018 confirm that indeed there are no detectable differences in power quality across the treatment and control sites. We report on this in more detail in our discussion of Evaluation Question 1 in section 3.2. Second, the sites must not have been chosen on the basis of any factors correlated with the outcomes of interest, which in our case are economic indicators. This would be a concern if, for example, the PMC incorporated economic indicators such as future growth in income or firm productivity when deciding where to inject new transformers. Through extensive conversations with the PMC, we feel confident that this was not the case. In addition, Section 3.2 presents extensive analyses comparing socioeconomic characteristics across the control and treatment sites, which show no difference at baseline. Therefore, any differences in power quality or economic outcomes between control and treatment sites observed at endline can be attributed to the transformer injections.

A third concern arises through potential geographic spillover effects. Line bifurcation investments at treatment sites might affect reliability and power quality at control sites through network effects. Given the geographic proximity of sites, it is possible that line bifurcation at treatment sites will reduce the load at nearby transformers which could be serving customers at control sites. To isolate network effects, we will compare reliability and power quality at control sites that are located far from any treatment sites with control sites that are located closer to clusters of treatment sites. The difference in power quality between control sites near treatment sites and control sites far from treatment sites would identify the impact of network effects. Importantly, this would only affect our ability to evaluate the impact of the investments on reliability and power quality. It would not affect our ability to rigorously evaluate the impact of changes in reliability and power quality on economic outcomes.

Finally, improvements in the electrical grid arising from other interventions under the Ghana Power Compact EFOT, such as the Outage Reduction Activity, Private Sector Participation Activity, or Modernizing Utility Operations Activity, may improve power quality and reliability across the entire city, including at control sites. Thankfully, an improvement in power quality at control sites would not pose a risk to our ability to evaluate the impact of the investments on reliability and power quality, because these investments would affect the treatment and control sites equally. We will therefore still be able to compare treatment against comparable control sites, and. Furthermore, we can leverage the high-frequency nature of GridWatch data. Using the PMC's construction progress data and our on-the-ground surveys we can compare power quality and reliability within a small temporal window, for example the week before and the week after the completion of line bifurcation at each specific treatment site. Using an event-study analysis framework we can pool these two-week windows across all sites use a rich set of fixed effects to identify the short-term impact of line bifurcation per se.

The effect of reliability may not scale linearly. It's possible, for instance, that for smaller differences in outages, customers are less likely to assume that they reflect systematic differences and so are less likely to make investment decisions on the basis of them. On the other hand, if the LV bifurcation improves voltage as well as outages, we may expect a larger effect size. The issue of linear effects of reliability on outcomes is less relevant to this evaluation as we will primarily evaluate the effects of dummy treatment variables. To the extent that we also conduct some analyses using continuous treatment variables (e.g., number or length of outages per period), we will explore heterogeneity in the treatment effect along this variable.

As the baseline survey precedes the completion of LB construction activities, this baseline report primarily presents descriptive statistics for outcomes of interest under each evaluation question, and discusses potential implications of baseline conditions for the evaluation. The baseline surveys were conducted across 76 line bifurcation injection (treatment) sites and 75 nearby control areas. During March to June 2021, the GridWatch team, along with sub-contractor Institute of Statistical, Social and Economic Research (ISSER), at the University of Ghana, conducted the baseline round of surveys 1,000 household and 1,000 firm surveys distributed across the 76 treatment and 75 control sites in Accra. Since the low voltage line bifurcation work was planned to be completed by early 2021 by the PMC, the endline surveys are planned for approximately 16-18 months after the baseline surveys (July-September 2022). This exposure period is long enough for customers to have adapted to the new levels of higher, improved reliability, but not so long that the impacts of the LV investments will have faded.

2.3 Data Sources

GridWatch Technical (Device) Data

Technical data on power reliability and quality is collected using the GridWatch suite of technologies, which in Accra consist of several hundred deployed PowerWatch devices, linked and analyzed through cloud computing software. PowerWatch devices have been deployed in line bifurcation sites since June 2018. These are the main source of data we rely on for testing whether treatment and control sites experienced similar patterns of electricity reliability prior to treatment, and to evaluate how reliability changes as a result of the line bifurcation injections. Currently, there are several hundred PowerWatch devices deployed in treatment and control areas for the line bifurcation work.

No other data source is available that can provide outage and voltage quality data at such a specific level of analysis as line bifurcation treatment and control sites. ECG outage data is defined at a much broader geographic level which makes it impossible to separate out treatment and control sites, as these are often located in close proximity to one another.

Primary Survey Data

The baseline and endline surveys target both households and firms in line bifurcation treatment and control sites. The household surveys collect information on socioeconomic characteristics of the household, including household size, income, and education of the respondent. The firm surveys collect information on business activities, revenues, and profits, as well as information on constraints firms face and measures taken in response to electricity reliability issues. For both firms and households, we also collect detailed data on their electricity usage, including electricity spending, appliance ownership and usage, ownership and usage of electricity protection devices, including generators, and impacts of reliability issues.

Sample size – We targeted a sample of 1,000 business and 1,000 households based on power calculations. This sample size should be sufficient to detect significant changes in key outcomes of interest as a result of the LB intervention.

Survey instrument – The household and firm survey instruments were developed based on well-tested existing instruments previously used by members of the GridWatch team in studies in other countries, as well as through pilots. (Annex B contains the final survey instrument.) The survey was further validated through piloting in non-sample areas of Accra prior to launch of the survey. The survey instrument covers 11 modules, such as household socio-demographic characteristics, firm characteristics, electricity usage and perceptions, and appliance ownership and use, and took between 1-1.5 hours to complete at baseline. The surveys were performed by a team of field officers using SurveyCTO on electronic tablets.

Survey sites – We conducted surveys in the 76 treatment sites identified by the PMC that will receive transformer injections in the districts of Achimota, Dansoman, and Kaneshie, and sampled an additional 75 control sites in these same districts. At each site, we drew a site boundary around the site location by following the grid network either for 300 meters from the location, or until reaching a point within 300 meters of an existing transformer. This approach was taken to ensure that we collected data from customers connected to parts of the grid most likely to benefit from the transformer LB injections.

We conduct between 10-15 surveys at each survey site, equally split between households and businesses. To select respondents at each site, we implemented a random walk sampling strategy in each site that aims to ensure that the sample is representative of the broader sample unit population. This method has been used in a large number of development economics studies and is accepted to generate a representative sample of the population. Enumerators begin at the site centroid and pick a random direction to begin walking, and approach every fourth household (every third in smaller sites) or business they encounter along their path until they have reached the target sample size for households and firms for the site. If they reach the site boundary, then they return to the starting point and pick a new random direction. Each random walk specifically targets either households or businesses. Budget and timing constraints prevented us from pursuing a listing of both households and businesses and the random sampling of respondents from those listings, but a well-implemented random walk ensures that the selection of respondents in each site is essentially random and representative.

All surveys were conducted within these boundaries. Survey staff were provided with the coordinates of the site location and with a map of the site boundary. In addition, the SurveyCTO electronic data collection was programmed to require enumerators to first collect the GPS coordinates of the location where they intended to conduct an interview, and to determine via an algorithm whether the location was inside or outside the site boundary. Coordinates outside the site boundary resulted in enumerators not being able to continue with the survey at that location and needing to return inside the boundary to collect new GPS coordinates at a different location.

Secondary Data

We complement primary data collection with several additional sources of secondary data. First, we obtained the most current and complete data on transformers and their attributes from the PMC, including load, location, and distance to furthest endpoint, for our study region. We used these data to determine which transformers (and their nearby customers) were likely to receive new infrastructure and which were less likely to receive new infrastructure. To determine whether LB injection decisions were adhered to, we obtained additional secondary data from the PMC during construction, listing where and when construction occurred, and what exactly was completed at each site, along with our ongoing on-site construction monitoring field surveys to verify this information independently.

We also compare characteristics of our study sample with data from the Ghana Statistical Services (GSS). Unfortunately, there is very little overlap between treatment and control sites for the LB intervention and locations of prior data collection by the GSS, meaning we cannot use these data to test for differences in socioeconomic outcomes in years prior to the start of LB construction. The primary use of these data is to determine how our survey samples of households and businesses compare to the broader population in Accra. For households, we consider data for urban households in the Greater Accra Region from the 2017 Ghana Living Standards Survey and the 2015 Labor Force Survey, which are representative of the population at the region and urban/rural levels. For businesses, we use data from the 2015 Integrated Business Establishment Survey for businesses in urban Accra with 30 or fewer employees, which are sampled randomly from the 2013 census of Ghanaian businesses. We obtained the original microdata for all 3 surveys from the GSS.

In addition, we are working with ECG to obtain data on outages at the feeder level for study areas to analyze general outage trends, and if possible, data on electricity consumption and expenditure for customers in study sites. If obtained, we will aim to include an analysis of the same in the endline report. The former data should be relatively easy to obtain, though their relevance to this analysis is limited since individual feeders may cover several of the treatment and control sites from our evaluation. Access to customer-level data has been discussed, with limited progress.

3. Findings

We begin with an overview of survey sample characteristics, as our findings draw almost exclusively on our survey data. We then present baseline descriptive results and findings for each of the seven evaluation questions in turn.

3.1 Survey summary statistics

This section presents summary statistics and general characteristics of the line bifurcation baseline survey household and business samples. The sample includes 998 households and 1004 businesses. To assess the representativeness of the samples, where possible we also show statistics from the population households and businesses in Accra using data from Ghana Statistical Service (GSS) surveys.

This section focuses on describing the samples of households and businesses that form the basis of the majority of the baseline analysis of the line bifurcation evaluation. While summary statistics for key outcomes of interest for these samples are relevant for understanding their characteristics, the findings sections covering the relevant evaluation questions provide more detailed discussions of these outcomes.

3.1.1 Households

Tables 2 and 3 present summary statistics of key variables for households in the line bifurcation baseline survey. Table 2 presents information on household and respondent characteristics, while Table 3 shows statistics for appliance ownership, electricity use and experiences, and alternative energy use.

Household Characteristics
The median household in the sample has 2 adults and 1 child, with both adults working paid jobs in the last 7 days and earning GHS 2500 (~USD 400) per month. The distribution of total household monthly income is shown in Figure 3, illustrating that nearly half of households earn less than GHS 1000 per month, and just 5% of households report incomes above GHS 7500.

Location characteristics
Concrete is the most common material for the walls of household dwellings (96%), and roofs are most commonly metal sheets (72%); these shares are similar to those from representative surveys of households in Accra.

Households have typically been at the same location for many years (the median is 6), but there is turnover. Forty-five percent of households rent their dwelling, similar to the 41% reported in GSS surveys, and pay an average of GHS 200 in rent (12.5% of monthly income for the median renting household). The remainder own their dwelling (31%) or occupy it rent-free (24%).

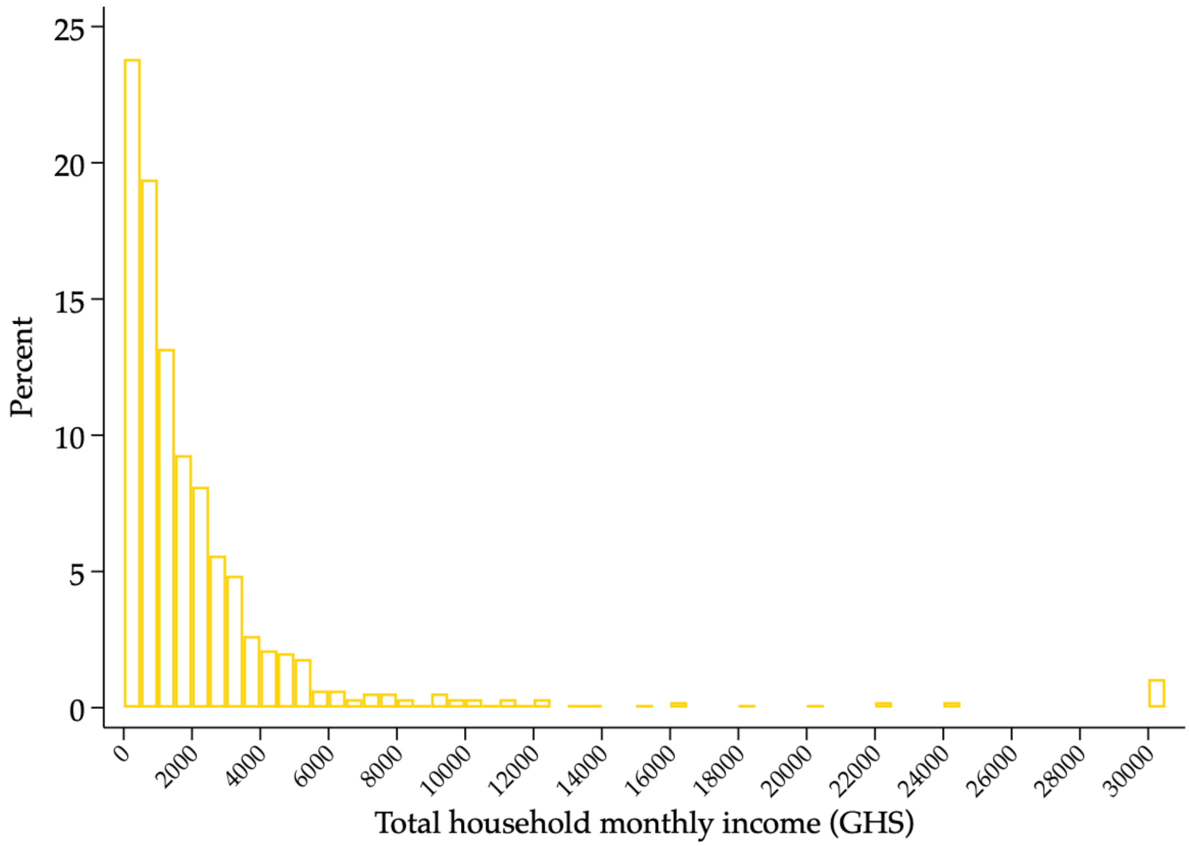
Respondent Characteristics
Household survey respondents are primarily female (61%) and just under 40 years old on average. Nearly all have completed primary schooling, and just over half have completed secondary school. GSS data on characteristics of household heads in Accra suggests that many of our survey respondents are not the heads of household, which reflects the survey methodology of surveying any available adult with knowledge of the households’ energy use and experiences.

Table 2. Household Summary Statistics: Household and Respondent Characteristics

	N	Mean	SD	Min	25th	50th	75th	Max	Accra Population Mean
Household characteristics									
Adult members	998	2.34	1.22	1	2	2	3	8	2.11
Child (<18) members	998	1.15	1.4	0	0	1	2	8	1.34
Share of teens (12-18) that completed primary school	314	0.91	0.27	0	1	1	1	1	
Total household monthly income (GHS)	949	3,801	42,579	0	500	1,200	2,500	1,300,600	5,252
Share of adults with paid jobs in last 7 days	998	0.67	0.36	0	0	1	1	1	
Location characteristics									
Primary roof material is metal sheets (=1)	998	0.72	0.45	0	0	1	1	1	0.48
Primary wall material is concrete (=1)	998	0.96	0.2	0	1	1	1	1	0.91
Number of years at location	967	10.75	10.13	0	3	6	17	31	
Rents premises (=1)	998	0.45	0.5	0	0	0	1	1	0.41
Monthly rent (GHS)	431	200.5	177.44	0	100	150	250	1200	
Respondent characteristics									
Respondent is male (=1)	998	0.39	0.49	0	0	0	1	1	0.67
Age (years)	998	39.53	11.92	18	30	37	48	65	45.39
Completed primary education (=1)	998	0.94	0.23	0	1	1	1	1	
Completed secondary education (=1)	998	0.52	0.5	0	0	1	1	1	
Completed post-secondary education (=1)	998	0.22	0.41	0	0	0	0	1	

Source: Baseline survey. Summary statistics for the population of households in Accra are taken from Ghana Statistical Service data from the 2017 Ghana Living Standards Survey or the 2015 Labor Force Survey for urban households in the Greater Accra Region and calculated using survey weights to generate representative estimates.
Notes: Missing values indicate the respondent answered “I don’t know” for a particular question or that it is not applicable. GHS 100 ≈ USD 16 at the time of surveying.

Figure 3. Distribution of Household Income



Source: Baseline survey. Monthly incomes are capped at GHS 30,000 to allow a more meaningful visualization. GHS 100 ≈ USD 16 at the time of surveying.

Appliance Ownership
Table 3 shows that households in the baseline survey own a variety of electric appliances, reporting just under 5 appliance types on average, where appliance types are categories of appliances such as televisions, fans, lamps, etc. Most households own mobile phones (2.3 on average), a refrigerator/freezer, a television, and a fan as the basic set of electric appliances.

Electricity
By design, all households in the sample are connected to the electricity grid. Nearly all are connected to a prepaid meter, meaning they must purchase electricity credit before consuming any electricity, and cannot use any electric appliances once their credit runs out. Just under half of households (46%) share their electricity meter, with a median of 3 other users, reflecting how common shared electricity connections are in this context. Most households report purchasing electricity for their meters themselves (at least on occasion if sharing a meter), but 14% report paying a landlord or someone else for their electricity. Households spend an average of GHS 104 (~USD 16) on electricity each month. Less than 3% report owning a generator.

Table 3. Household Summary Statistics: Appliance Ownership and Electricity and Alternative Energy Use

	N	Mean	SD	Min	25th	50th	75th	Max	Accra Population Mean
Appliance ownership									
Total count of appliance types owned	998	4.80	2.85	0	3	4	6	20	
Count of mobile phones	998	2.34	1.46	0	1	2	3	10	3.02
Any fridge at location (=1)	998	0.74	0.44	0	0	1	1	1	0.62
Any television at location (=1)	998	0.90	0.29	0	1	1	1	1	0.85
Any fan at location (=1)	998	0.94	0.25	0	1	1	1	1	
Any air conditioner (AC) at location (=1)	998	0.13	0.34	0	0	0	0	1	
Electricity									
Electricity from prepaid meter (=1)	998	0.99	0.11	0	1	1	1	1	
Count of meter users	994	2.32	2.33	0	1	1	3	20	
Pays someone else for electricity (=1)	998	0.14	0.35	0	0	0	0	1	
Monthly electricity spending (GHS)	990	103.92	104.75	0	40	80	120	1000	95.88
Has generator (=1)	998	0.03	0.16	0	0	0	0	1	0.02

Source: Baseline survey. Summary statistics for the population of households in Accra are taken from Ghana Statistical Service data from the 2017 Ghana Living Standards Survey or the 2015 Labor Force Survey for urban households in the Greater Accra Region and calculated using survey weights to generate representative estimates.
Notes: Missing values indicate the respondent answered "I don't know" for a particular question or that it is not applicable. GHS 100 ≈ USD 16 at the time of surveying.

Comparison of Sample Characteristics to GSS Data on Accra Households

In general, the household survey sample appears to be broadly representative of the urban population of Accra, with the exception of households in the highest-income areas. Household size is similar to the average across all households in Accra based on GSS data from 2017, a similar share of households are renters, and main wall and roof materials are similar. Statistics for electricity spending and ownership of common appliances are very similar to the GSS surveys. Higher TV and refrigerator ownership may reflect increased access to these appliances in the 4 years since the Ghana Living Standards Survey, and the fact that the study sample only includes households with electricity connections.

The main difference is in mean income, which is significantly lower in the sample (the same is true for median income). The survey measure of household income is constructed by asking for the total income for each working household member (one question per working adult), converting it to a monthly amount, and taking the sum for the household. The GSS's Ghana Living Standards Survey 7 measure is constructed analogously, but the questions on individual household members' work and income are much more detailed, asking specifically about different jobs and different forms of earnings. So, the large gap in estimated household income between the two sources may represent differences in survey design. The difference may also reflect effects of the Covid-related economic crisis, which may have reduced work participation and average incomes. Finally, and perhaps most relevantly, the gap may represent differences in sampling. Survey areas did not include high-income residential areas, instead focusing mainly on mixed residential-business areas. The GSS surveys are intended to be representative of the population so should include more higher-income households.

3.1.2 Businesses

Summary statistics of key variables for businesses in the line bifurcation baseline survey are shown in Tables 4 and 5. Table 4 presents information on business and respondent characteristics, while Table 5 shows statistics for appliance ownership, electricity use and experiences, and alternative energy use.

Table 4. Business Summary Statistics: Business and Respondent Locations and Characteristics

	N	Mean	SD	Min	25th	50th	75th	Max	Accra Population Median
				Business characteristics					
Total employees	1004	1.99	2.11	0	1	1	2	25	7
Share of male employees	1000	0.31	0.42	0	0	0	1	1	0.74
Share of full-time employees	985	0.92	0.21	0	1	1	1	1	
Usual business open hours	1004	12.03	2.52	0	10	12	14	24	
Open during non-daylight hours	1004	0.76	0.43	0	1	1	1	1	
Total profit in past month (GHS)	777	716	1,597	-3,600	160	400	800	30,000	29,623
Total revenue in past month (GHS)	870	3,462	21,183	0	600	1,200	3,000	600,000	115,000
Total measured business costs in past month (GHS)	817	2,293	7,530	10	435	990	2,100	204,000	
				Location characteristics					
Primary roof material is metal sheets (=1)	1004	0.80	0.4	0	1	1	1	1	
Primary wall material is concrete (=1)	1004	0.46	0.5	0	0	0	1	1	
Number of years at location	977	6.58	6.67	0	2	4	9	31	
Rents premises (=1)	1004	0.49	0.5	0	0	0	1	1	
				Respondent characteristics					
Respondent is male (=1)	1004	0.31	0.46	0	0	0	1	1	
Age (years)	1004	37.76	10.91	18	30	37	45	65	
Completed primary education (=1)	1004	0.95	0.22	0	1	1	1	1	
Completed secondary education (=1)	1004	0.51	0.5	0	0	1	1	1	
Completed post-secondary education (=1)	1004	0.13	0.33	0	0	0	0	1	

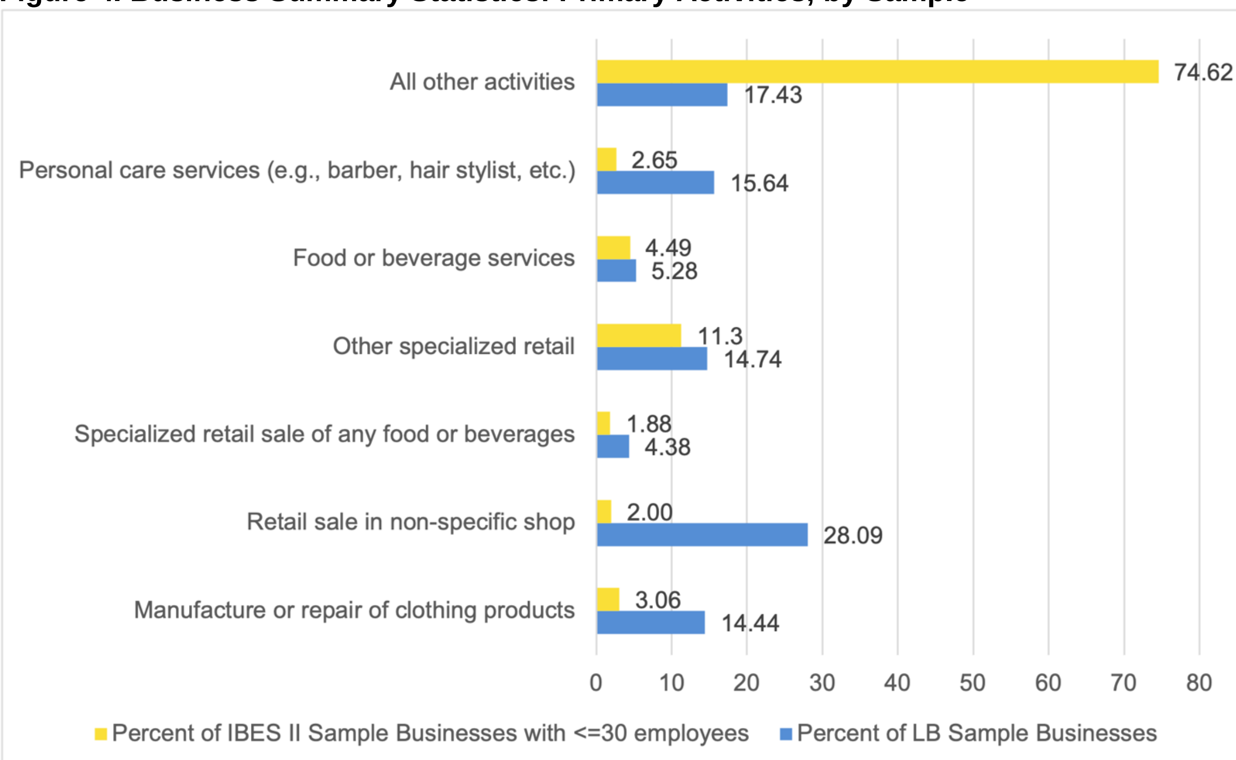
Source: Baseline survey. Summary statistics for the population of businesses in Accra are taken from Ghana Statistical Service data from the 2015 Integrated Business Establishment Survey II for businesses in urban Accra with 30 or fewer employees, which are sampled randomly from the 2013 census of Ghanaian businesses.
Notes: Missing values indicate the respondent answered "I don't know" for a particular question or that it was not applicable. GHS 100 ≈ USD 16 at the time of surveying.

Business Characteristics
This study focuses on small and medium-sized businesses with 30 or fewer employees, and in practice the samples are skewed toward very small businesses with 1 or 2 employees. Many of the businesses are small owner-operated firms, and a significant portion also share a structure with the household that

operates the business: 11.8% of businesses in the sample. Just over half of businesses have just one worker, and another 30% have two workers. Nearly all businesses (97%) have five or fewer employees. Thirty-one percent of employees are male, which aligns with the share of male business respondents - unsurprising since most businesses have just 1 worker. Among businesses with more than 1 worker, 42.7% have all female employees, 21.7% have all male employees, and 35.6% have a mix of men and women. Nearly all employees (92%) are reported to be working full-time for the business.

Baseline sample businesses are typically open for 12 hours per day, and 76% are open at least some hours while it is dark. Businesses have been at the same location an average of 6.6 years, and just under half rent their business location. Businesses most commonly have concrete walls (46%) and metal roofs (80%). The most common other wall material is metal (45%), reflecting the fact that 47% of businesses are located in repurposed shipping containers. Another 8% of businesses have stand-alone kiosks, while 14% have commercial space in a single-story building.

Figure 4. Business Summary Statistics: Primary Activities, by Sample

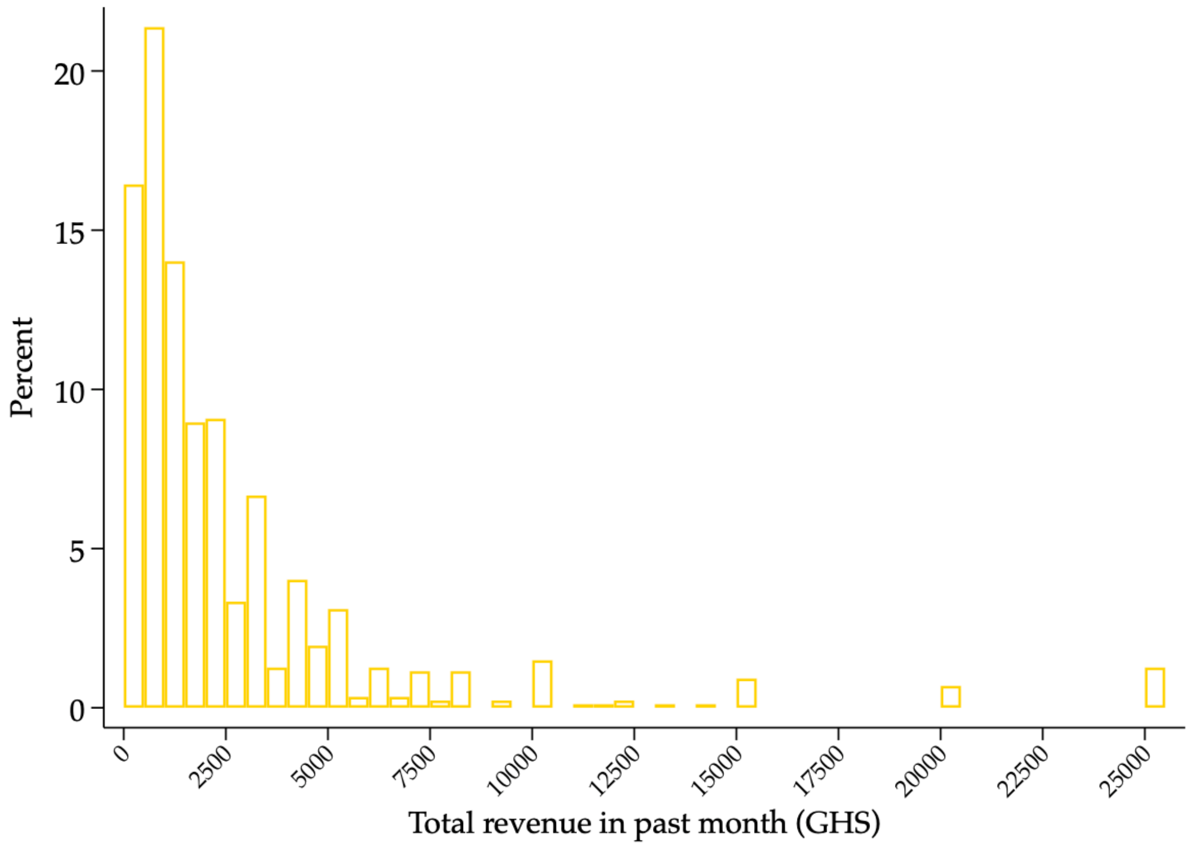


Source: 2021 baseline survey (blue) and 2015 Integrated Business Establishment Survey Round II (gold). The IBES II data includes businesses in urban Accra with 30 or fewer employees, which are sampled randomly from the 2013 census of Ghanaian businesses.

Primary Business Activities

These employment statistics reflect the nature of businesses sampled in the baseline survey. Figure 4 shows the five most common primary business activities in the baseline survey, the share of businesses in those activities, and the sum of the shares of businesses in other specialized retail activities, alongside the share of businesses with fewer than 30 employees in Accra in those industries, using data from the GSS's 2015 Integrated Business Establishment Survey Round II (IBES II). The surveys overrepresent businesses involved in the production of clothing (e.g., tailors and seamstresses), personal care (e.g., barbers and hair stylists), non-specific general retail sale (e.g., small corner kiosks), and specialized food and beverage retail sale (e.g., cold stores and water vendors). The share of businesses engaged in all other forms of specialized retail are, however, similar in the two samples. These activities account for 83% of businesses in the baseline survey sample of businesses, compared to 25% of businesses with less than 30 employees in Accra in the IBES II. We discuss reasons why the baseline sample is not representative of business activities in Accra at the end of this section.

Figure 5. Distribution of Business Revenues in Past Month



Source: Baseline survey. Reported revenues capped at GHS 25,000 to allow a more meaningful visualization. GHS 100 ≈ USD 16 at the time of surveying.

Profits and Revenue

Just over three-quarters of business respondents provided an estimate of their total profit in the past month, with a mean of GHS 717 (~USD 114) on revenues of GHS 3,462 (~USD 551). Median profits are GHS 400 on revenues of GHS 1,200. Profits were elicited by directly asking respondents to estimate their total profit after paying all expenses, following best practices established in the literature (de Mel, McKenzie, & Woodruff 2008). Around 85% of respondents provided estimates of revenues and of specific costs (not intended to be comprehensive). Figure 5 shows the distribution of business revenues in the past month, with values above the 99th percentile capped at the value for the 99th percentile. The distribution illustrates how the majority of businesses in the survey are quite small: 72% report earning less than GHS 2,500 (~USD 400) in the past month. Businesses report expenditures of GHS 2,293 (~USD 365) on average in the past month across employee wages, materials, and energy, though estimates of these costs are missing for around 18% of businesses.

Appliance Ownership

Table 5 shows that businesses report fewer appliance types than households, likely reflecting the specialized nature of most businesses. The most common appliances are similar to those for households. The prevalence of TVs and refrigerators/freezers in the sample reflects the nature of the sampled businesses: most are small shops providing services or conducting small retail operations.

Table 5. Business Summary Statistics: Appliance ownership and Electricity Usage (Line Bifurcation Sample)

	N	Mean	SD	Min	25th	50th	75th	Max	Accra Population Median
					Appliance ownership				
Total count of appliance types owned	1004	3.00	2.06	0	2	3	4	19	
Count of mobile phones	1004	1.97	1.76	0	1	1	2	20	
Any fridge at location (=1)	1004	0.49	0.50	0	0	0	1	1	
Any television at location (=1)	1004	0.52	0.50	0	0	1	1	1	
Any fan at location (=1)	1004	0.75	0.43	0	0	1	1	1	
Any air conditioner (AC) at location (=1)	1004	0.08	0.27	0	0	0	0	1	
Any non-electric business machines	1004	0.09	0.29	0	0	0	0	1	
					Electricity				
Electricity from prepaid meter	1004	0.99	0.09	0	1	1	1	1	
Count of meter users	997	1.55	1.17	0	1	1	2	20	
Pays someone else for electricity (=1)	1004	0.07	0.26	0	0	0	0	1	
Monthly electricity spending (GHS)	983	123.95	326.87	0	42	80	120	8000	1200
Has generator (=1)	1004	0.05	0.22	0	0	0	0	1	

Source: Baseline survey. Summary statistics for the population of businesses in Accra are taken from Ghana Statistical Service data from the 2015 Integrated Business Establishment Survey II for businesses in urban Accra with 30 or fewer employees, which are sampled randomly from the 2013 census of Ghanaian businesses. IBES II data are fairly limited, so we do not have comparison values for most variables in this table.
Notes: Missing values indicate the respondent answered "I don't know" for a particular question or that it was not applicable. GHS 100 ≈ USD 16 at the time of surveying.

Most businesses do not own *productive appliances*; appliances potentially used for providing goods and services. The most common, reported by 15% of businesses, is electric sewing machines or other clothing-related machines, consistent with 14% of businesses being engaged in clothing-related activities. Just 9% of businesses report having any non-electric machines for business purposes, the most common of which are manual (i.e., foot pedal-operated) sewing machines.

Electricity

As with households, nearly all businesses are connected to a prepaid electricity meter (Table 5). Sharing a meter is less common for businesses: 63.6% have their own meter. Businesses are also more likely to pay for electricity themselves rather than paying an intermediary and spend GHS 124 (~USD 20) per month on electricity. For the median business reporting different types of business costs, electricity represents 8.3% of their reported business spending. Businesses are slightly more likely than households to report having a generator (5% compared to less than 3%).

Comparison of Sample Characteristics to GSS Data on Accra Businesses

We compare statistics for our sample to median values for businesses in Accra with 30 or fewer employees, from the GSS 2015 Integrated Business Establishment Survey Round II (IBES II) which includes a representative sample of all businesses from a 2013 national business census. Although the IBES II business data include very few of the variables in the baseline survey, limiting our ability to comparison, it does include several key variables, including industry, employment, revenues, profits, and electricity spending.

Unlike the comparison of sample household means to Accra population means, here we observe significant differences between sample business means and the median for a representative sample of small and medium-sized Accra businesses. Figure 4 makes clear that the distribution of primary business activities is very different in the baseline survey sample. In the baseline survey, the median number of employees is 1 and the 75th percentile is 2. In the IBES II, among businesses with 30 or fewer employees the median number of employees is 7 and the 75th percentile is 15. Unsurprisingly given that IBES II businesses are much larger and engaged in different activities, median monthly business revenues and profits are 30 to 40 times larger in the IBES II data, while electricity spending is around 10 times larger. However, even for the sample of IBES II businesses with two or fewer employees, reported revenues and profits are larger. This may reflect differences in business activities, differences in survey design, or effects of the COVID-19 pandemic on business revenues.

We believe the differences we observe are largely due to a difference in sampling. First, the line bifurcation evaluation sites generally exclude business-focused areas, instead covering areas with mixed residential and business structures. Larger and more formal businesses would likely primarily be concentrated in non-residential areas. Second and more importantly, the baseline survey includes a large number of household and informal businesses that might have been missed in the IBES business census, which explicitly sought to include informal businesses but excluded mobile businesses, traders in open spaces, and non-permanent trading units. The IBES II also stratified sampling by number of employees, oversampling large firms and under-sampling firms with a small number of employees. Unfortunately, the IBES II data do not include survey weights to account for this. The difference in samples is clear from the differences in the primary industries of the businesses.

In summary, the sample of businesses in the baseline survey is not similar to the sample of small and medium non-household enterprises in Accra included in the IBES. It is not clear, however, given the lack of a comparable dataset with survey weights, how representative the sample might be of all small and medium household and non-household enterprises in Accra. Given the distribution of number of employees, the baseline samples might be considered as primarily representative of small businesses in Accra, and therefore any findings may not generalize to other types of businesses, particularly medium and large enterprises.

3.1.3 Baseline balance tests

This section compares baseline characteristics for households and businesses in LB treatment sites and those in control sites. The purpose of these tests is to check whether the samples appear balanced on observed characteristics at baseline before any exposure to the LB treatment. There are 479 households and 500 businesses in control sites and 519 households and 504 businesses in LB treatment sites.

Across most socioeconomic variables, household and business characteristics are well-balanced between sites, which indicates that the selection of control sites to serve as counterfactuals for treatment sites was successful. Section 3.2.2 tests for balance at baseline in measures of electricity reliability. This section focuses on the small set of characteristics that differ significantly by treatment status at baseline.

Table 6. Balance in Means by Treatment Status: Energy Use and Location Characteristics

	Household Means		Business Means	
	Control	Treatment	Control	Treatment
Energy Use				
Monthly electricity spending (GHS)	110.26	95.77**	109.38	101.58
Has generator (=1)	0.03	0.03	0.05	0.06
Used charcoal as fuel in past 3 months (=1)	0.67	0.64	0.16	0.16
Used gas as fuel in past 3 months (=1)	0.82	0.79	0.20	0.22
Used no fuels in past 3 months (=1)	0.02	0.03	0.74	0.69
Spending on alternative fuels in average month (GHS)	63.59	62.96	31.51	38.59
Main source of lighting is lightbulbs (=1)	0.89	0.87	0.89	0.88
Any electricity protective devices (=1)	0.31	0.29	0.19	0.21
Total count of appliance types owned	4.86	4.74	3.04	2.96
Location Characteristics				
Primary roof material is metal sheets (=1)	0.71	0.74	0.81	0.78
Primary wall material is concrete (=1)	0.95	0.96	0.48	0.43
Number of years at location	10.49	10.99	6.66	6.49
Rents premises (=1)	0.46	0.43	0.45	0.52*
Monthly rent among renters (GHS)	193.13	205.92	-	-

Source: Baseline survey. Stars indicate significance of t-tests for differences in means, with * p<0.1, ** p<0.05, *** p<0.01.

Table 6 shows that means for variables relating to energy use and location characteristics are balanced between treatment and control respondents at baseline for both households and businesses. An exception is monthly electricity spending, which is GHS 14.49 (USD 2.21) greater in control households than treatment households, a difference of around 13%. This does not jeopardize any of the endline analyses, which will test for differences in changes in key outcomes of interest, which controls for baseline differences such as this one. The endline analysis will test whether this gap decreases following exposure to the LB treatment, which is hypothesized to increase electricity spending. The only other variable in the table that varies by treatment status is the share of businesses that rent the premises, which is seven percentage points higher in treatment sites, although this difference is only weakly significant: when testing multiple outcome variables simultaneously, one can expect approximately 10 percent of outcomes to be significant at the 10 percent level purely by chance.

Table 7. Balance in Means by Treatment Status: Additional Household and Business Characteristics

	Control Mean	Treatment Mean	Difference C-T	p-value
Households				
Adult members	2.33	2.35	-0.02	0.81
Child (<18) members	1.15	1.14	0.01	0.89
Total household monthly income (GHS)	2344.72	2199.91	144.81	0.57
Share of adults with paid jobs in last 7 days	0.66	0.68	-0.01	0.54
Businesses				
Business engaged in retail activities	0.42	0.44	-0.02	0.60
Business engaged in clothing activities	0.15	0.13	0.02	0.39
Business engaged in personal care activities	0.15	0.16	-0.01	0.58
Total employees	2.04	1.93	0.12	0.38
Share of male employees	0.32	0.30	0.02	0.35
Share of full-time employees	0.91	0.92	-0.01	0.51
Usual business open hours	12.07	11.99	0.09	0.58
Open during non-daylight hours	0.76	0.76	-0.01	0.83
Total profit in past month (GHS)	667.76	631.19	36.58	0.58
Total revenue in past month (GHS)	2561.09	2578.45	-17.36	0.95
Total reported business costs (GHS)	2060.43	2507.55	-447.12	0.43

Source: Baseline survey.

Table 7 illustrates that key household and business characteristics are balanced at baseline. In no case do the p-values suggest that the differences are even close to being statistically significant.

In general, these balance tests indicate that households and businesses in treatment and control sites appear similar at baseline. Any differences between treatment and control sites observed in the endline surveys can therefore be attributed to the LB treatment, rather than other differences between the sites.

3.2 Evaluation Question 1

> *What is the impact of the infrastructure investments of the ECG Project on the reliability of power in areas of Accra targeted by the line bifurcation and network upgrades? Did the infrastructure improvements result in increased power available to customers, reduce the frequency and duration of outages, and improved voltage stability?*

This question relates to Stage 2 of the program logic causal chain presented in Section 1.1, relating to short-term outcomes of the line bifurcation infrastructure improvements. The immediate objective of these improvements is to improve electricity reliability, with the broader goal that improved reliability leads to improved socioeconomic outcomes. The hypothesis is therefore that treatment sites receiving network infrastructure improvements will both have more stable voltage and frequency and experience fewer and shorter service interruptions as a short-term outcome, relative to otherwise similar control sites receiving no improvements.

Construction for the LB improvements largely took place from late 2020 through the first few months of 2021. It is therefore too soon to be able to confidently measure the impact of LB infrastructure improvements on power reliability. Nevertheless, Sections 3.2.1 and 3.2.2 present and explore patterns for power reliability in the data from two sources: (i) objective data from GridWatch devices and (ii) respondent recall data from the baseline survey. The data shared by ECG cannot be used for this analysis as it is not disaggregated at the level of treatment and control sites, though if the detail of ECG changes in the future it may be possible to see if broad improvements in power reliability can be detected as a result of LB construction.

3.2.1 GridWatch data

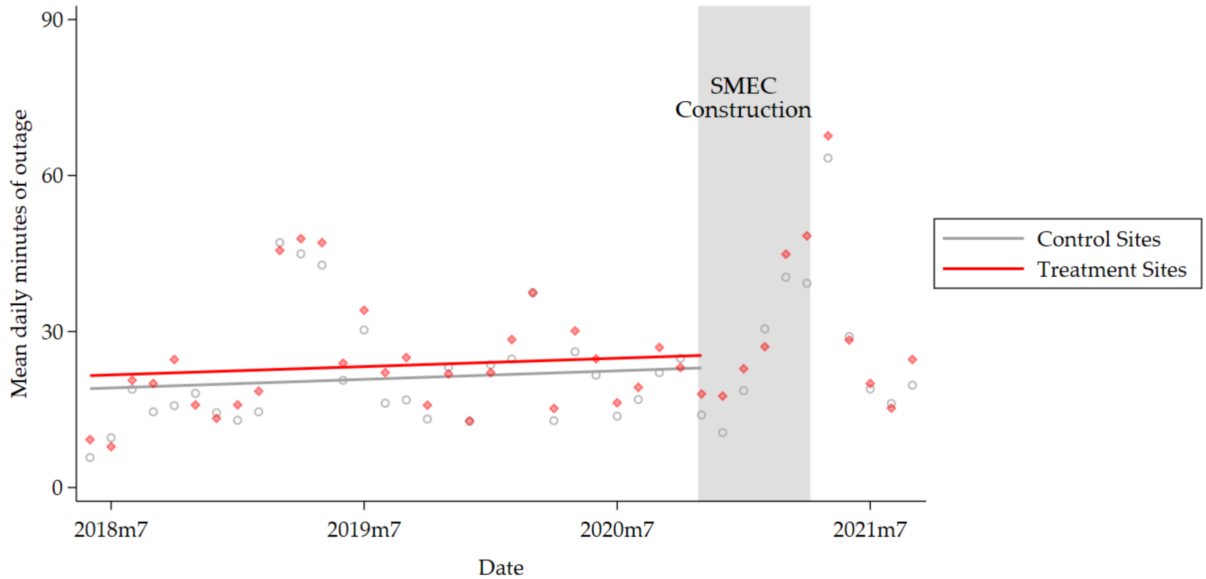
Summary:

1. *GridWatch devices deployed across treatment and control sites since June 2018 allow us to visualize trends in reliability over time by site line bifurcation treatment status.*
2. *Measures of reliability—mean daily outage minutes and the share of devices reporting bad voltage—exhibit seasonal fluctuations, but follow nearly identical trends in treatment and control sites prior to line bifurcation construction work in late 2020.*
3. *Changes in reliability by treatment status post-construction could thus reasonably be attributed to line bifurcation improvements.*
4. *Data from the short period with data post-construction suggest improvements in reliability in both treatment and control sites, but larger in treatment sites.*
5. *We take this as initial evidence of improvements in reliability from line bifurcation activities. The endline report will present longer time series of GridWatch data and more formal tests of changes in measured power reliability over the full post-construction exposure period.*

GridWatch devices deployed across treatment and control sites collect detailed and objective data on measures of power reliability with data going back to June 2018. These data allow us to check whether treatment and control sites follow similar trends in reliability measures prior to the SMEC line bifurcation construction activities, and to identify any changes by treatment status post-construction.

We first consider trends in daily outage duration over time across treatment and control sites, shown in Figure 6. The red line of linear fit represents the treatment sites and the grey line represents the control sites. These lines overlap almost perfectly and follow a slight upward trajectory in the period prior to SMEC construction from June 2018 to November 2020, showing that average daily outage duration did not differ between treatment and control sites. Seasonal fluctuations are also similar across sites. This finding is reassuring as it corroborates the evaluation strategy and ensures that any comparison between baseline and endline outcomes could directly be attributed to the intervention of infrastructure investments in LB sites.

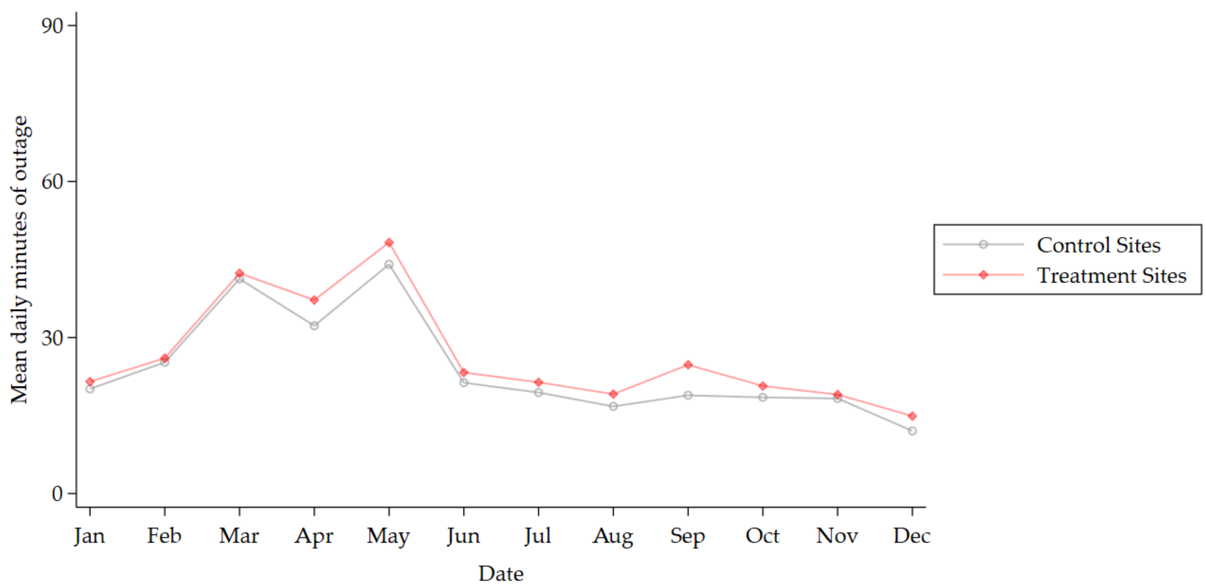
Figure 6. Mean Daily Outage Duration Over Time, by Site Treatment Status



Source: GridWatch devices

The figure also shows preliminary evidence of changes in outages post-construction. Treatment and control sites both experienced high levels of outages at the end of construction period which fell in subsequent months, similar to the pattern observed at this time of year in 2019. It is important to note that, since construction took place relatively recently, we currently have insufficient data to analyze the post-construction data with any statistical confidence.

Figure 7. Average Monthly Outage Hours by Month (2018-2020), by Site Treatment Status



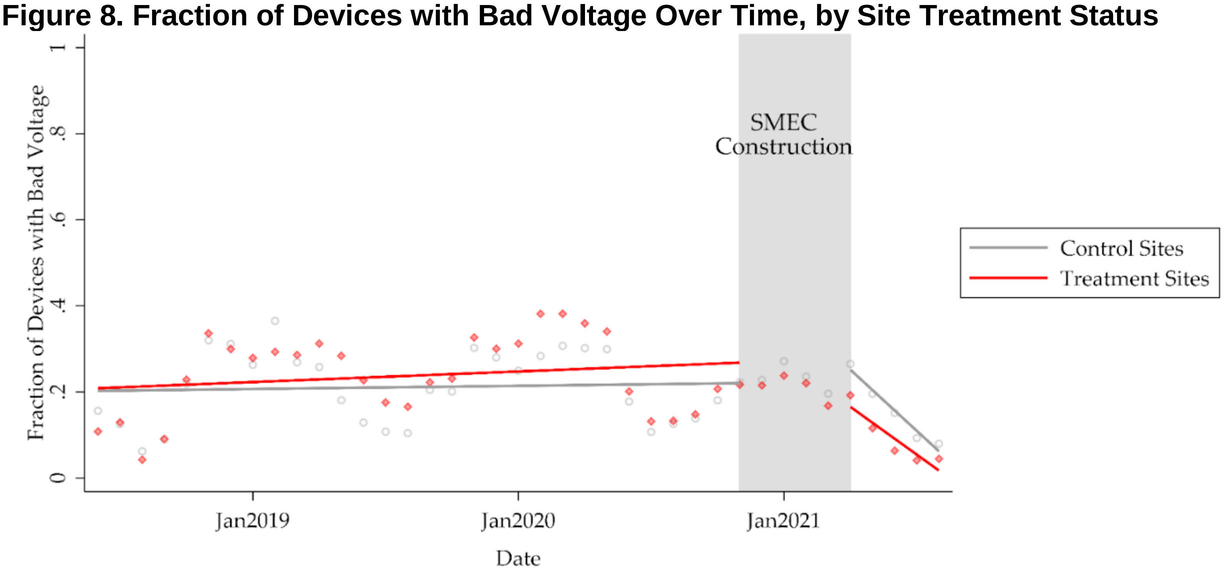
Source: GridWatch devices

To illustrate the seasonality in outage hours, Figure 7 shows average outage hours by month and site treatment status across 3 years (2018-2020) per the GridWatch devices. Seasonal trends are similar in treatment and control sites. Average monthly outage hours are highest from March-July. Higher outages in March coincide with the highest average monthly temperatures in Accra. The period of higher outages partially overlaps with the period of higher average temperatures (November-May), and may reflect higher load on the electricity grid from increased use of cooling appliances, as high load can lead to increased faults. It is noteworthy that customers experience more outages in March and April, as this is the time period for the baseline household and business survey, meaning survey reports of outages may be higher than they would be at other times of year.

The GridWatch technology can also shed light on the type of power outages experienced by respondents. When an HV feeder outage occurs, a significant area of Accra experiences an outage at the same time, and as a result a large share of GridWatch devices would detect an outage at the exact same time. Conversely, when an LV outage occurs (for example, due to an overloaded distribution transformer), a much smaller number of GridWatch devices would report an outage. The LB intervention can be expected to affect transformer overload, and thus reduce LV outages, but is unlikely to directly reduce the number of HV outages. GridWatch uses sophisticated techniques to determine the type of outage experienced by customers.

We next consider trends in voltage quality over time by site treatment status. International engineering standards define voltage to be of poor quality as being more than 10% above or below nominal voltage. Ghana's nominal voltage is 230, meaning voltage would be considered "bad" if it is below 207 or above 253. Voltage quality is expected to be one of the primary forms of reliability affected by the line bifurcation improvements due to the reduced electricity loads in parts of the grid receiving LB treatment. Figure 8 plots the mean daily share of devices with bad voltage by site status, and shows lines of best fit for trends in bad voltage for treatment sites (in red) and control sites (in gray).

Figure 8. Fraction of Devices with Bad Voltage Over Time, by Site Treatment Status



Source: GridWatch devices

Treatment sites appear to have had very similar voltage quality on average prior to LB construction: a formal statistical test finds no differences in voltage quality or in outage duration between treatment and control sites. Reassuringly for the evaluation strategy, treatment and control sites exhibit similar trends in this measure of power reliability prior to LB construction. The share of devices with bad voltage fluctuates over time, but treatment and control sites experience the same fluctuations, suggesting control sites represent good counterfactuals for the changes in reliability in treatment sites absent treatment.

In addition to validating the evaluation design, this figure also provides preliminary progress towards answering evaluation question 1. After LB construction, treatment sites had better voltage quality than

control sites in each month from April-August 2021. This is evidence that LB infrastructure improvements are having the intended impact of improving electricity reliability, in terms of voltage quality. While voltage quality in the control group also appears to have improved between May-September 2021, this improvement does not appear different than the previous annual cycles that can be observed at the same time in previous years, thus we currently do not interpret this as a treatment effect on control sites. In Section 2.2 Evaluation Methodology we describe our strategy should the decrease in the control persist.
The endline report will present longer time series of GridWatch data and more formal tests of changes in these measures of power reliability across treatment and control sites.

3.2.2 Survey data

Summary:

1. *Survey respondents report on their electricity reliability experiences—count of outages, average outage duration, and average daily hours of bad voltage—over the past 30 days.*
2. *Treatment and control sites are balanced in reported electricity reliability at baseline. Respondents in treatment sites report slightly more outage hours over the past month and average daily hours of bad voltage than respondents in control sites, but the differences are not statistically significant.*
3. *The results indicates that respondents in treatment sites had not yet perceived any improvements in power reliability relative to those in control sites at the time of the baseline survey, which came during the period LB construction was being completed.*
4. *The endline report will test whether reported reliability measures differ significantly by treatment status after a longer exposure period.*

This section presents data from GridWatch devices and measures of power reliability from the baseline survey. As baseline survey data were collected from March-April 2021, around the time LB construction was being completed, these data cannot answer the research question about the impacts of infrastructure improvements on reliability. A more complete analysis of the effects of LB construction on measures of electricity reliability will be possible after the endline survey. Nevertheless, the baseline survey can allow us to test for baseline balance between respondents in treatment and control sites.

Household and business respondents are asked several questions about their electricity quality over the past 30 days. However, some respondents may not accurately recall their reliability experience. These data should therefore be interpreted as measuring respondents' *perceptions* of power reliability. The endline report will compare respondent recall on electricity reliability to matched data from GridWatch devices in the same sites.

Table 8: Balance in Means for Reliability Measures, by Site Treatment Status

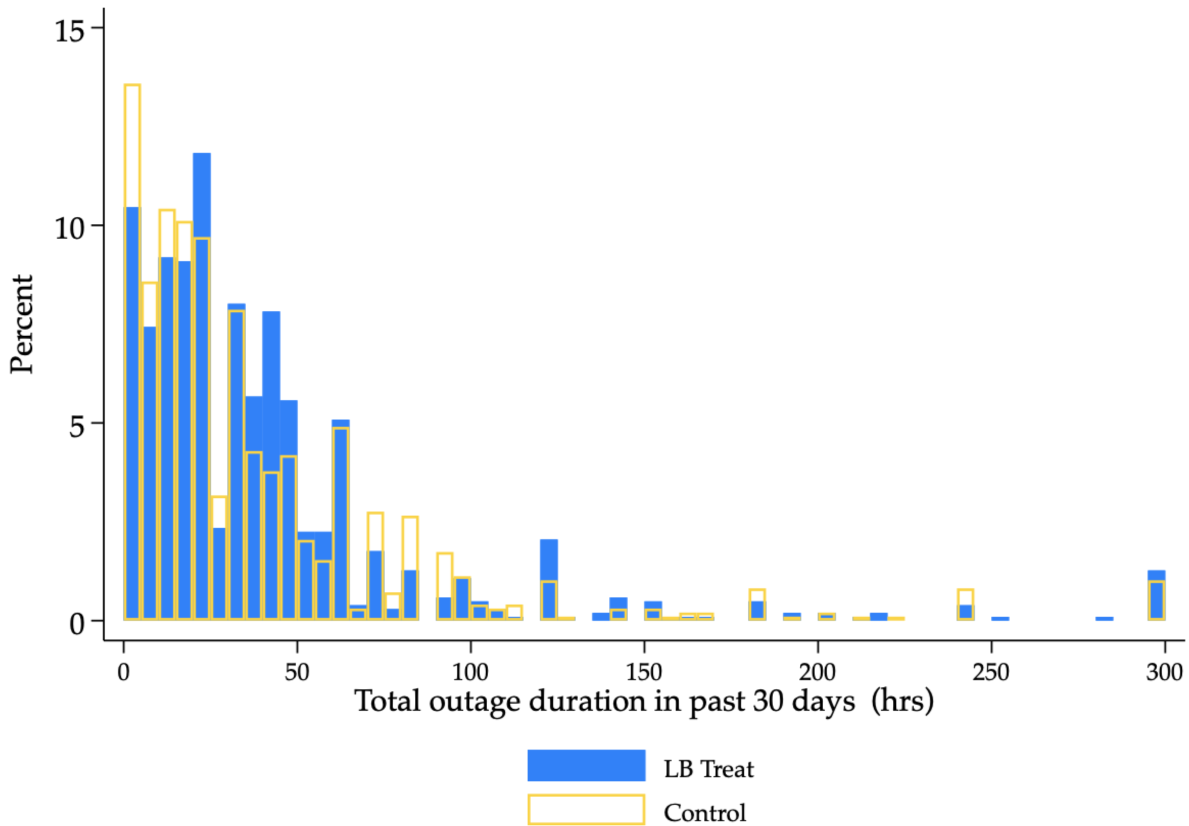
	Control Mean	N	Treatment Mean	N	Difference C-T	p-value
Count of outages in past 30 days	7.00	979	6.73	1023	0.27	0.26
Total outage duration in past 30 days (hours)	39.72	979	42.17	1023	-2.45	0.37
Average bad voltage hours per day in past 30 days	1.48	974	1.70	1015	-0.22	0.14

Source: Baseline survey

Table 8 presents results of tests of balance between mean responses across control and treatment sites for four measures of power reliability. Respondents in control sites report an average of 7 outages in the past 30 days, compared to 6.73 in treatment sites, but this difference is not significant. Respondents in treatment sites report 42.17 total outage hours in the past 30 days, 2.45 hours (6.2%)

more than in control sites, though this is again not significant. This difference appears consistent with Figure 6, which shows similar outage minutes per day in treatment sites relative to control sites prior to the LB construction. Respondents in treatment and control sites also report similar hours of bad voltage per day over the past 30 days, consistent with GridWatch data in Figure 8 for the pre-construction period.

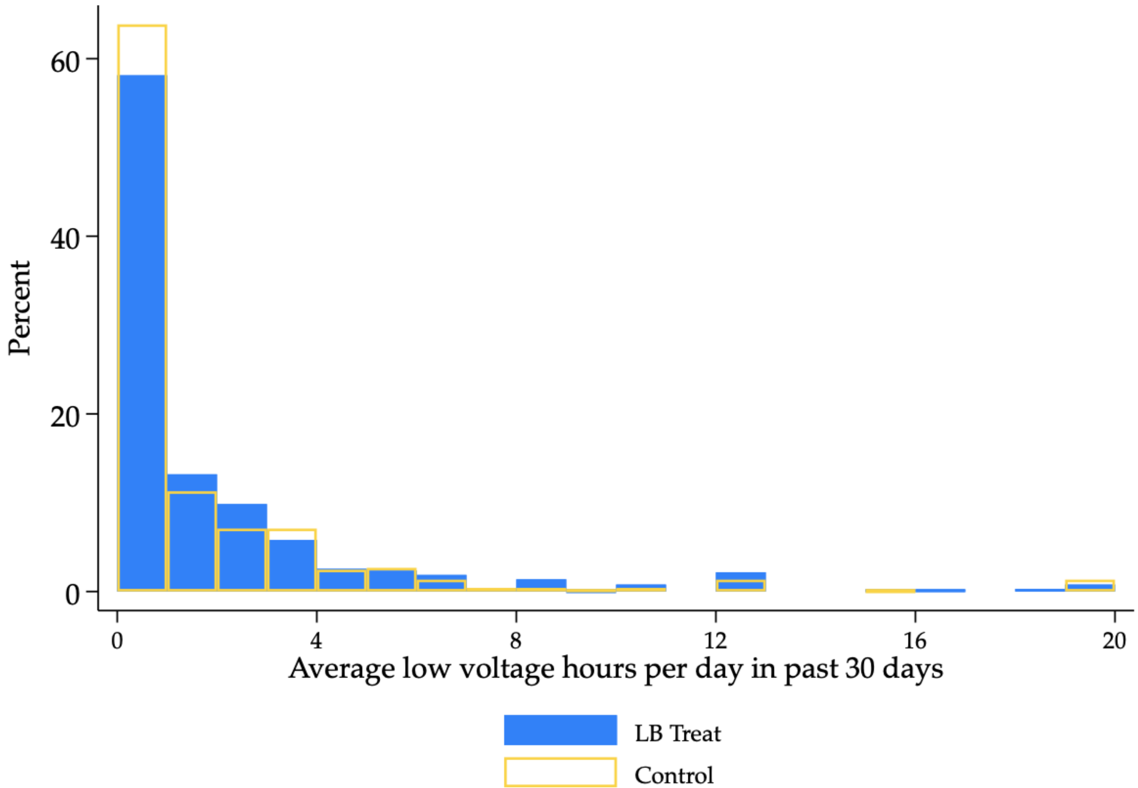
Figure 9: Distribution of Respondent Recall Total Outage Hours in Past 30 Days, by Site Treatment Status



Source: Baseline survey

Figures 9 and 10 show the distribution of responses for two of these measures of reliability, total outage hours in the past 30 days and average daily bad voltage hours in the past 30 days, by site treatment status. They illustrate that the distributions are similar for the two groups.

Figure 10: Distribution of Respondent Recall Average Daily Bad Voltage Hours in Past 30 Days, by Site Treatment Status



Source: Baseline survey

The impact of LB treatment on measures of reliability can be thought of as the "first stage" underlying any effect of treatment on other outcomes. Table 9 presents "first stage" regressions using baseline survey data of the above measures of power reliability.

Table 9: Regressions of Reliability Measures on Site Treatment Status

	Count of outages in past 30 days	*Average outage duration in past 30 days (hours)*	*Total outage duration in past 30 days (hours)*	*Average bad voltage hours per day in past 30 days*
LB Treatment	-0.181	0.610	2.780	0.235
	(0.394)	(0.451)	(4.243)	(0.227)
Control Mean	6.966	5.487	39.716	1.479
Observations	1998	1998	1998	1985

Source: Baseline survey.

Notes: Columns indicate the outcome variable in the regressions. Outcome values are trimmed at the 99th percentile. Rows report estimated coefficients for regressions of the outcome on LB treatment and additional controls. Additional controls included but not displayed in the output for simplicity include a dummy for whether the tenant is a household or a business, respondent age, sex, and level of education, dummies for whether the tenants own or rent the premises, a dummy for whether the tenants pay a landlord for electricity or manage their meter directly, a dummy for having a generator, the count of mobile phones owned at the premises, the count of different appliance types owned at the location, and the latitude and longitude for the survey site centroid. Standard errors clustered at the site level are included in parentheses. Asterisks indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Results in Table 9 are from regressions including a set of location and respondent controls but showing only the coefficients for the effect of LB treatment, and with standard errors clustered at the site level.

Results are qualitatively the same in simple bivariate regressions including only a dummy variable for LB treatment. Note that the sign for the effect of LB treatment flips relative to Table 8, because the difference there is the effect of being in a control site while regression coefficients are the effect of being in a treatment site.

Differences by treatment status are similar to the simple differences in means, even after including controls, and are again uniformly not significant. This indicates that respondents in treatment sites had not yet perceived any improvements in power reliability at the time of the baseline survey and that power quality is similar across sites at baseline. The challenge to answering this evaluation question using survey data will be to analyze if customers have been able to observe and accurately recall reliability improvements at the time of the endline survey after a longer line bifurcation exposure period.

3.3 Evaluation Question 2

> *What are the economic and socio-economic benefits of access to reliable power on customers, including households and enterprises? How are these benefits distributed?*

This question forms the core of the impact evaluation, broadly considering the long-term economic outcomes of the line bifurcation improvement activities reflected in Stage 3 (and, to an extent, Stage 4) of the causal chain within the program logic (Section 1.1). The analysis of this evaluation question will estimate differences between control and treatment sites while controlling for any observed baseline differences. To the extent that poor reliability was constraining optimal energy use, by the endline survey at the end of exposure period, enough time should have gone by for changes in electricity usage and any economic benefits associated with improved electricity usage to have become observable.

This baseline report identifies outcome variables of interest for this question and presents initial descriptive statistics. The baseline survey alone is not sufficient to address the distribution of benefits. The endline survey will enable an analysis of economic impacts of LB treatment as well as an analysis of how the impacts vary by baseline household income and by baseline business revenue.

We present baseline findings for this evaluation questions under three sub-sections: (i) business energy usage, (ii) household energy usage, and (iii) household outcomes. We focus first on analyzing energy usage for businesses and households: electricity spending, spending on mechanisms to deal with poor reliability, and use of alternative energy sources. We discuss ownership and use of electric appliances under evaluation question 4 which specifically considers investments in power-consuming technology. We then report on measures of household well-being related to changes in energy usage that may be expected to change during the project exposure period: use of electricity for cooking and for studying. Other household outcomes may change in the longer term due to improved energy usage (Stage 4 of the program logic), but such changes are unlikely to be observed by the time of the endline survey. We discuss impacts on economic outcomes for businesses under evaluation question 5 which specifically considers impacts of the project on business outcomes and mechanisms behind these impacts.

3.3.1 Business Energy Usage

Summary:

1. *Few businesses in the sample report alternative energy sources besides electricity.*
2. *Five percent have a generator, almost none have solar panels or wet cell batteries.*
3. *Those using a generator use it for 20 hours a month and spend around USD 18 on fuel and maintenance.*
4. *Seventy-two percent of businesses report not using any fuels for energy in the past 3 months.*
5. *Twenty-one percent used gas and 16% used charcoal; use is more common among businesses in food and beverage-related activities.*
6. *Mean monthly electricity spending is around USD 20 per month, compared to USD 6 for all other energy sources.*
7. *Twenty percent of businesses report owning devices to protect against electricity reliability issues. The most common protective devices are fridge guards (14% of businesses with refrigerators) and stabilizers (14% of all businesses).*
8. *Twenty-four percent of businesses report appliances being damaged due to voltage fluctuations in the past 12 months, costing an average of USD 33 to repair or replace.*

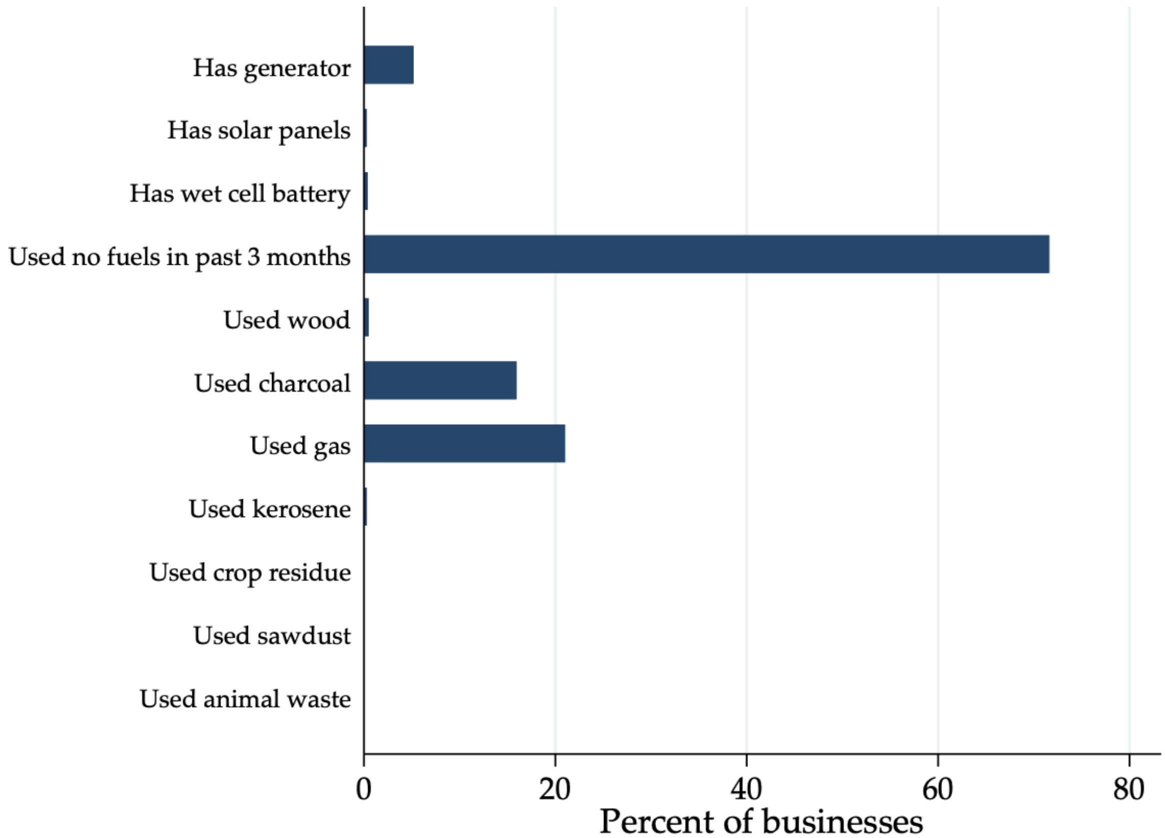
Energy Sources and Spending

In addition to detailed questions about electricity use, the baseline survey includes questions about alternative energy sources (generators, solar panels, and wet cell batteries) and about fuels used for energy. The list of fuels asked about is drawn from other household surveys administered in Ghana. Reassuringly, in general there are no significant differences at baseline in energy use among businesses by treatment status. Businesses in control sites are 5 percentage points more likely to say they used no fuels in the past 3 months for energy (74% compared to 69% in treatment sites). Aside from this, the samples of control and treatment businesses are similar at baseline.

While all businesses in the sample must be connected to electricity, some also use alternative sources of energy. But use of alternative energy sources is limited, as illustrated in Figure 11 below. Few businesses own machines allowing them to produce electricity directly rather than relying on the grid: generators (5.2%), solar panels (0.3%), or wet cell batteries (0.4%). This may reflect the nature of businesses in the sample as not being heavily dependent on energy use. For example, 37% are engaged in retail or food and beverage service. However, there is no clear pattern indicating ownership of these alternative energy sources is more common in certain sectors than in others.

Among the 52 businesses with a generator, 31 (59.6%) report having used it in the past 3 months, for an average of 20 hours per month. The modal business with a generator reports using it only a few times per year (26.9%). Just 13 businesses with generators (23.1%) report using it more than once a month. Among owners using a generator in the past 3 months, mean monthly spending on fuel and maintenance is GHS 115 (~USD 18). We explore generator use during outages in more detail in response to evaluation question 3, but these low rates of generator use among generator owners reflect that most report only sometimes using their generator when there is a power outage.

Figure 11. Share of Businesses with Different Alternative Energy Sources and Using Different Fuels in Past 3 Months



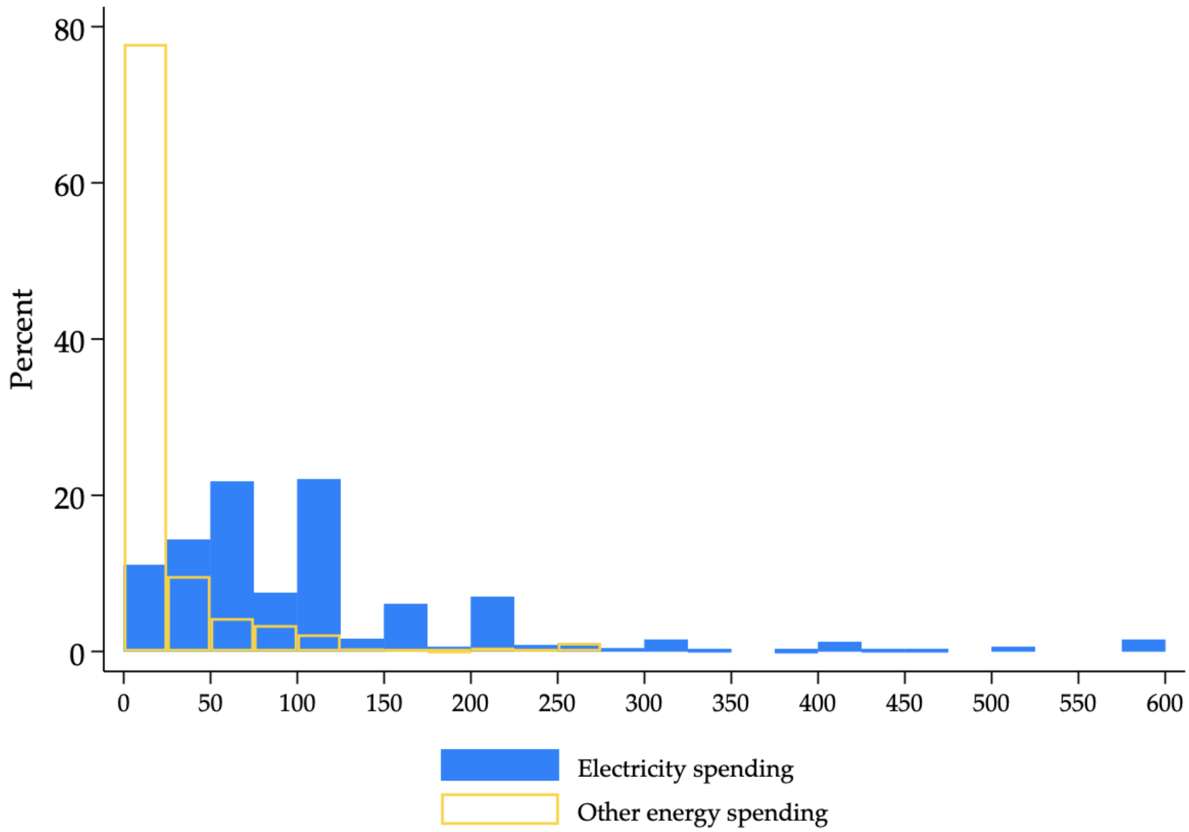
Source: Baseline survey.
Note: The question about fuel use is "In the past three months, what types of alternative fuels/energy sources have you or someone else at this household or business used at this location?" This would appear to exclude fuel consumed outside the location, for example, fuel for a vehicle or motorcycle.

As shown in Figure 11, most businesses (71.6%) did not use any other fuels for energy in the past 3 months. Charcoal (15.9%) and gas (21.0%) are the most commonly used. A small number of businesses use wood (0.5%) or kerosene (0.3%), and none report using crop residue, sawdust, or animal waste as fuels. The fuel categories included in the baseline survey are taken from a Ghanaian survey targeting both rural and urban areas, and it was expected that use of these latter fuels would likely be very low in in urban Accra.

As with alternative electricity sources, low use of fuels that could be an alternative to electricity may reflect the nature of businesses in the sample as not particularly energy-intensive. Use of charcoal is most common for business in the food/beverage services (41.5%) and retail of food/beverages (43.2%), suggesting use of this fuel in food preparation. Use of gas is also common in these two industries (47.2% and 38.6% of businesses, respectively), likely for the same reason. There are no other clear patterns in which industries are more likely to use these fuels.

Sample businesses spend an average of GHS 123.9 (USD 19.7) per month on electricity, with a median of 80. This compares to an average of GHS 35.1 (USD 5.6) and a median of 0 per month for alternative energy sources in total, including spending on all alternative fuels, on generator fuel, and on maintenance for generators and other alternative energy sources. Figure 12 shows the distribution of business spending on electricity and other fuels in the past month, with values for each capped at the value for the 99th percentile. The figure illustrates the large share of businesses not spending anything on other energy sources.

Figure 12. Distribution of Business Monthly Spending on Electricity and Other Energy Sources (GHS)



Source: Baseline survey. GHS 100 ≈ USD 16 at the time of surveying.

In summary, businesses in this sample do not appear to commonly use alternative forms of energy beyond electricity. We explore the implications of low use of these alternatives to electricity during power outages in response to Evaluation Question 3.

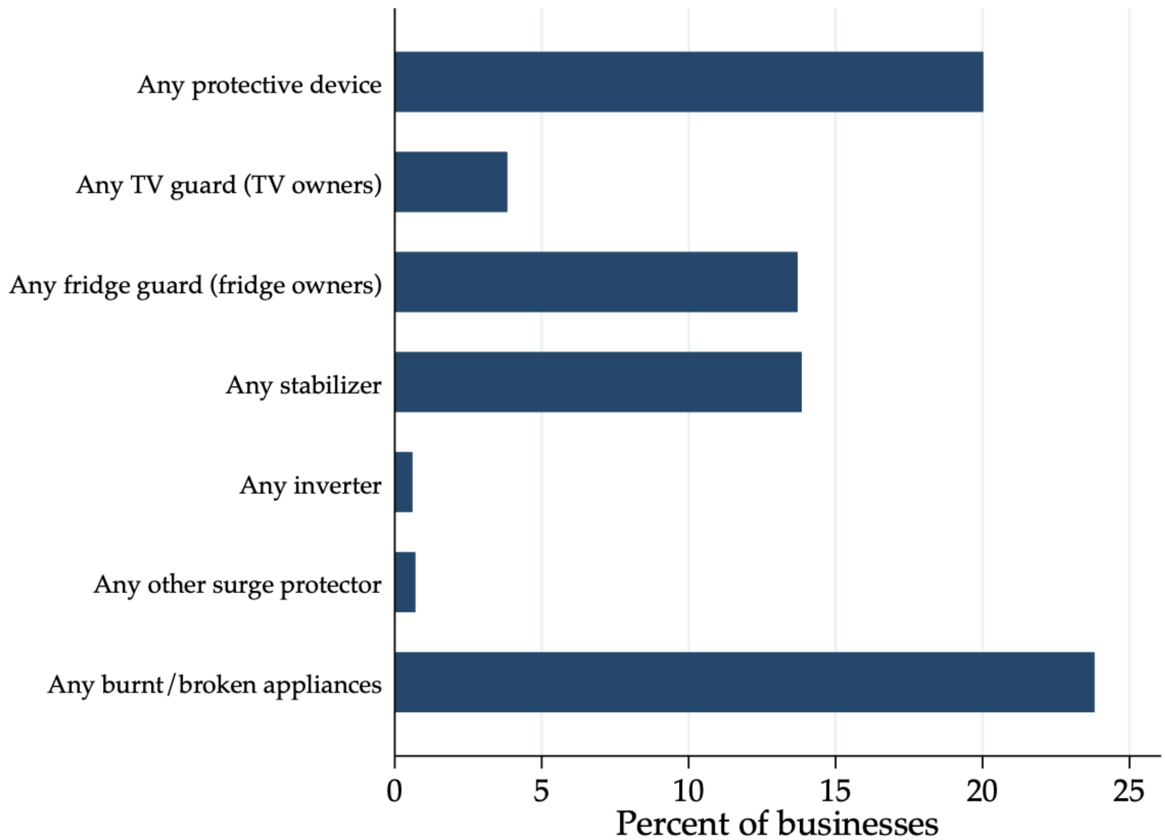
Given the low share of businesses owning a generator (let alone solar panels or wet cell batteries), it may be difficult to identify any significant changes in use of alternatives to electricity due to the line bifurcation treatment. Use of alternative fuels is slightly more common, but appears linked to business practices (namely, food preparation) so may not change in response to improved electricity reliability. The most likely outcomes where we expect to see change at the end of the exposure period are electricity spending, which we hypothesize will increase in treatment site businesses relative to control site businesses, and total spending on alternative energy sources, which we hypothesize will fall.

Protective Device Ownership

Customers may benefit from reliability improvements by reducing their investment in devices to protect from reliability issues, such as voltage stabilizers or fridge guards. Such investments are a direct response to poor reliability, so become less useful when reliability improves. The baseline survey asks respondents about their ownership of a variety of protective devices. Ownership is balanced between businesses in treatment and control sites at baseline.

Figure 13 summarizes information on protective device ownership and experiences with voltage-related damages among sample businesses. Most businesses (80%) do not report owning any devices to protect against electricity reliability issues. The most common protective devices are stabilizers (14% of businesses). Although 14% of businesses with refrigerators or freezers report having a fridge guard, just 11% of business fridges are reported to be protected against voltage fluctuations with fridge guards suggesting they are not always used.

Figure 13. Business Ownership of Protective Devices and Experiences with Voltage-related Damages



Source: Baseline survey.

High ownership of protective devices may reflect high perceived risk of damages from poor reliability. Twenty-four percent of businesses report having any appliances damaged (burnt or broken) due to voltage fluctuations in the past 12 months. Businesses spent an average of GHS 48.4 (USD 7.7) to repair or replace damaged appliances over this period, though among businesses who actually experienced damages the average is GHS 205.1 (USD 32.6). This represents over 1.5 months of average electricity spending so is not trivial, but may not be sufficient to motivate all businesses to pay the up-front investment cost for protective devices.

We hypothesize that damages to appliances due to voltage fluctuations and associated spending will fall by the end of the exposure period for businesses in line bifurcation treatment areas relative to those in control areas. We do not expect to observe any change in ownership of protective devices.

3.3.2 Household Energy Usage

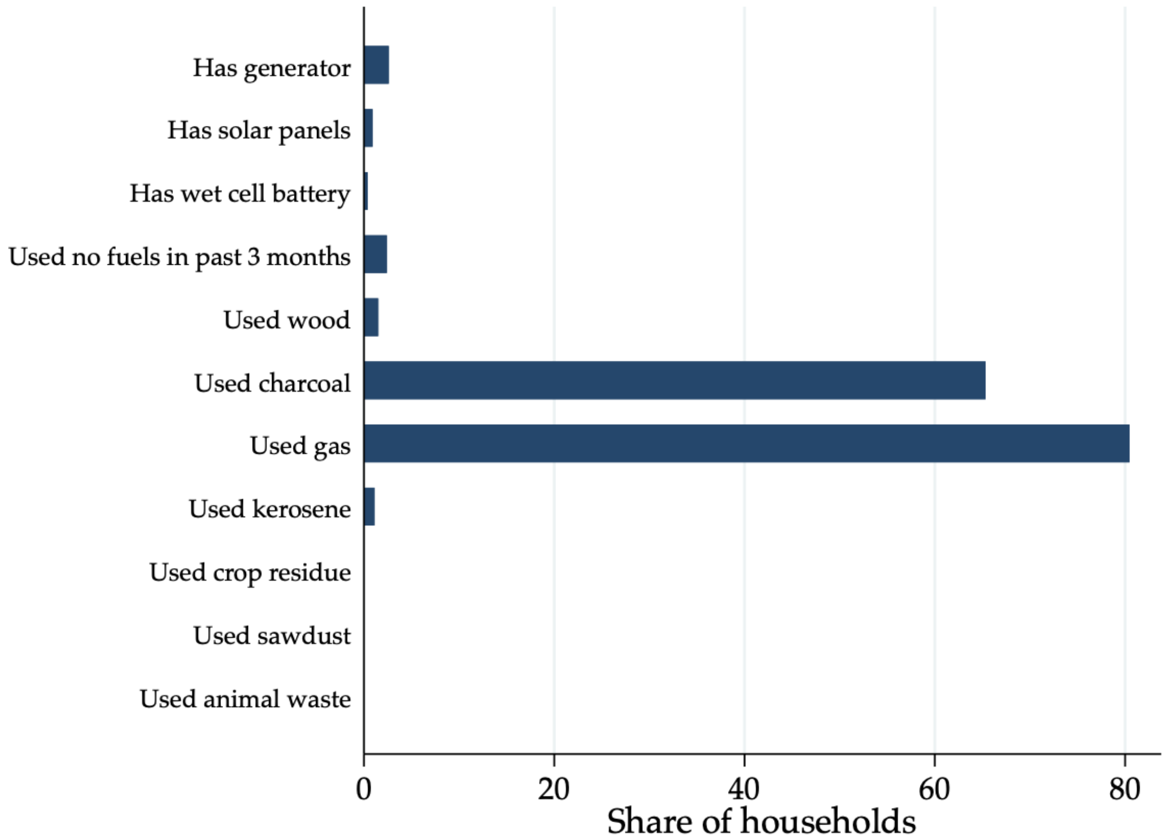
***Summary*:**
1. *Few households in the sample report alternative sources of electricity. Only 2.6% of households have a generator, almost none have solar panels or wet cell batteries.*
2. *Generators are not used frequently, with 77% of owners not using it in the past 3 months.*
3. *Households use on average between 1 and 2 other fuels for energy besides electricity.*
4. *Eighty-one percent use gas and 65% use charcoal, and use appears primarily tied to cooking where these are the primary energy sources for nearly all households.*
5. *Mean monthly electricity spending is around USD 16 per month, compared to USD 10 for all other energy sources, indicating more diversified energy spending than for businesses.*
6. *About one-third of households report owning devices to protect against electricity reliability issues, but rarely own more than one type of device.*
7. *The most common protective devices are fridge guards (20% of households with refrigerators) and stabilizers (15% of households).*
8. *Twenty-nine percent of households report appliances being damaged due to voltage fluctuations in the past 12 months, costing an average of USD 47 to repair or replace.*

Energy Sources and Spending

Few households in the sample report owning alternative sources of electricity (Figure 14). Just 2.6% have a generator, 0.9% have solar panels, and 0.4% have a wet cell battery. These shares are similar across treatment and control sites. Low ownership of such alternative electricity sources may reflect the relatively low incomes and appliance ownership levels in the household sample. Median household income and electricity income are both higher for households with generators, suggesting this may indeed be the case.

Among 26 households with a generator, just 23.1% report having used it in the past 3 months, for an average of 7.7 hours per month. This is much lower than the use by businesses, perhaps because households are less reliant on electricity than businesses. The modal household with a generator reports using it only a few times per year (42.3%). Just 5 (19.2%) report using their generator more than once a month. Among the few owners using a generator in the past 3 months, mean spending on fuel and maintenance is GHS 103 (~USD 16). We explore the implications of low ownership and use of generators and other alternative electricity sources during power outages in response to Evaluation Question 3.

Figure 14. Share of Households with Different Alternative Energy Sources and Using Different Fuels in Past 3 Months



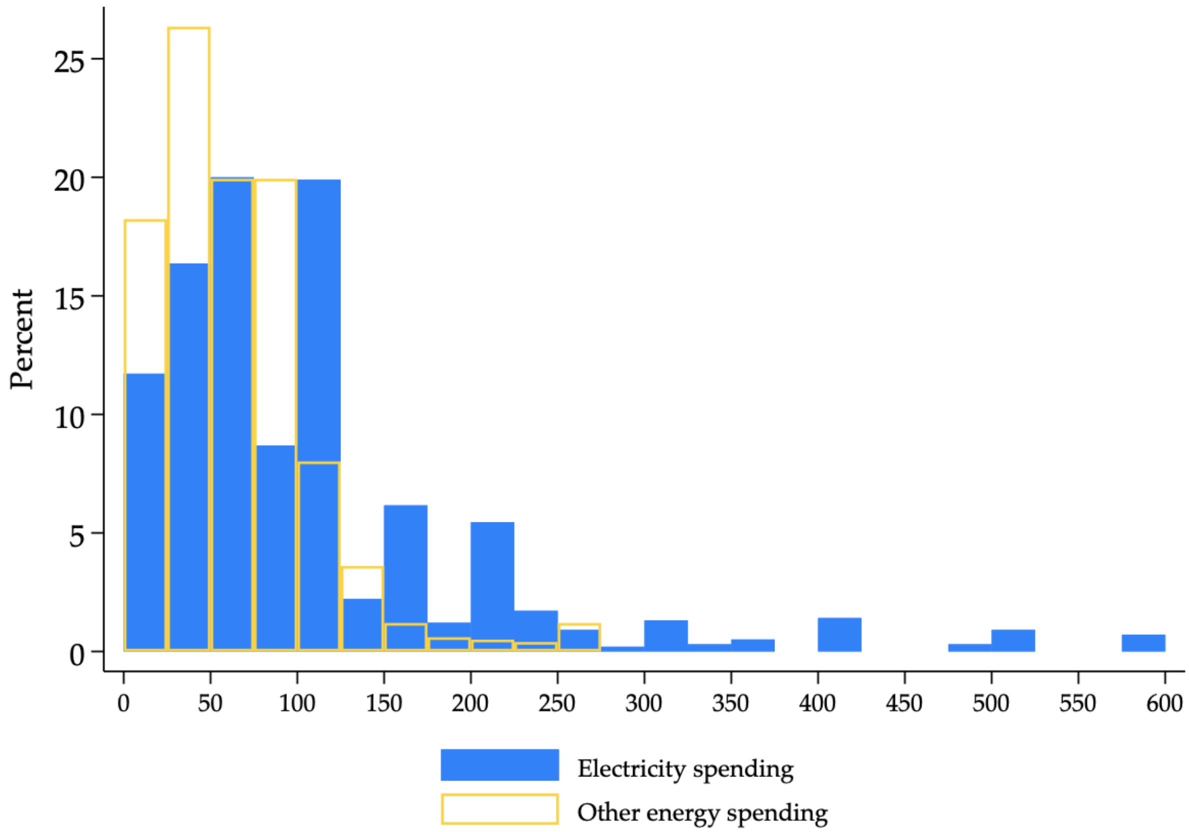
Source: Baseline survey.

In addition to electricity, households in the baseline sample frequently use alternative sources of energy, as illustrated in Figure 14. Unlike businesses, households typically report between 1 and 2 fuels used in the past 3 months besides electricity. The most common are again charcoal (65.3%) and gas (80.5%). Wood is used by 1.5% of households and kerosene by 1.1%. None use crop residue, sawdust, or animal waste as fuels, reflecting the urban study setting. Reported fuel sources are similar across treatment and control households.

High use of charcoal and gas among households reflects their prevalence in food preparation. 64.0% of households report using charcoal for cooking in the last 3 months and 80.2% report using gas, accounting for nearly all of households' use of these fuels.

Sample households spend an average of GHS 103.9 (USD 15.9) per month on electricity, with a median of 80. This compares to an average of GHS 63.3 (USD 9.7) and a median of 50 per month for alternative energy sources in total, primarily on alternative fuels. This represents a different energy mix than for businesses, with 59% of household energy spending going to electricity on average compared to 89% for businesses. Figure 15 shows the distribution of household spending on electricity and other energy sources in the past month, with values for each capped at the value for the 99th percentile. The figure illustrates the much higher use of other energy sources among households relative to that shown for businesses in Figure 11.

Figure 15. Distribution of Household Monthly Spending on Electricity and Other Energy Sources (GHS)



Source: Baseline survey. GHS 100 ≈ USD 16 at the time of surveying.

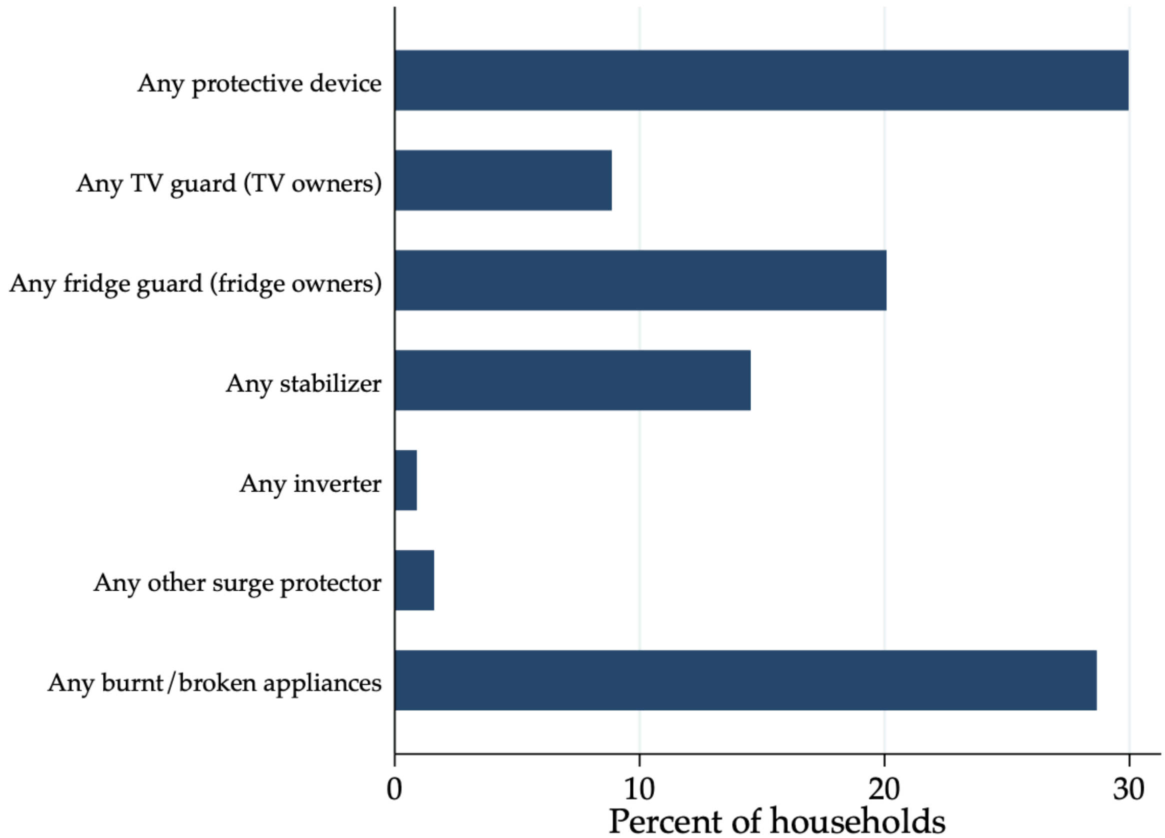
Households in control sites spend significantly more on electricity each month than treatment households (GHS 112 compared to 96 GHS), but spend a similar amount on other energy sources. To the extent that improved reliability increases electricity consumption and spending in treatment sites, we hypothesize that the gap in monthly electricity spending would close. Since other energy sources are used primarily for cooking, we would not expect to see treatment affect other energy spending unless reliability were a key reason households use alternative fuels for cooking, which does not appear to be the case here.

Protective Device Ownership

Customers invest in devices such as voltage stabilizers or fridge guards to help protect against damages caused by poor reliability (voltage fluctuations in particular), so become less useful when reliability improves. Figure 16 summarizes protective device ownership and experiences with damage from voltage fluctuations among sample households in the baseline survey.

Thirty percent of households report owning at least one protective device, and ownership is balanced between treatment and control sites. As with businesses, the most common protective devices are stabilizers (15% of households), though 14.6% of all households (20% of those with fridges/freezers) own fridge guards. The share of fridges protected by fridge guards (18%) is a bit lower than the share of households with both fridges and fridge guards, primarily due to a few households with more fridges or freezers than fridge guards.

Figure 16. Household Ownership of Protective Devices and Experiences with Voltage-related Damages



Source: Baseline survey.

Low use of protective devices may reflect low perceived risk of damages from poor reliability, but such damages appear fairly common and costly. Twenty-nine percent of households report having any appliances damaged (burnt or broken) due to voltage fluctuations in the past 12 months. Households spent an average of GHS 85.6 (USD 13.1) over this period to repair or replace damaged appliances, though these costs do not include the loss of appliances that are damaged by voltage fluctuations but not repaired or replaced, which are reported by 9.7% of households. Among households who actually experienced damages the average spending to repair or replace them is GHS 306.2 (USD 46.8). This represents nearly 3 months of average household electricity spending, but may not be sufficient to motivate households to pay the up-front investment cost for protective devices.

We hypothesize that damages to appliances due to voltage fluctuations and associated spending will fall by the end of the exposure period for households in line bifurcation treatment areas relative to those in control areas. We do not expect to observe any change in ownership of protective devices.

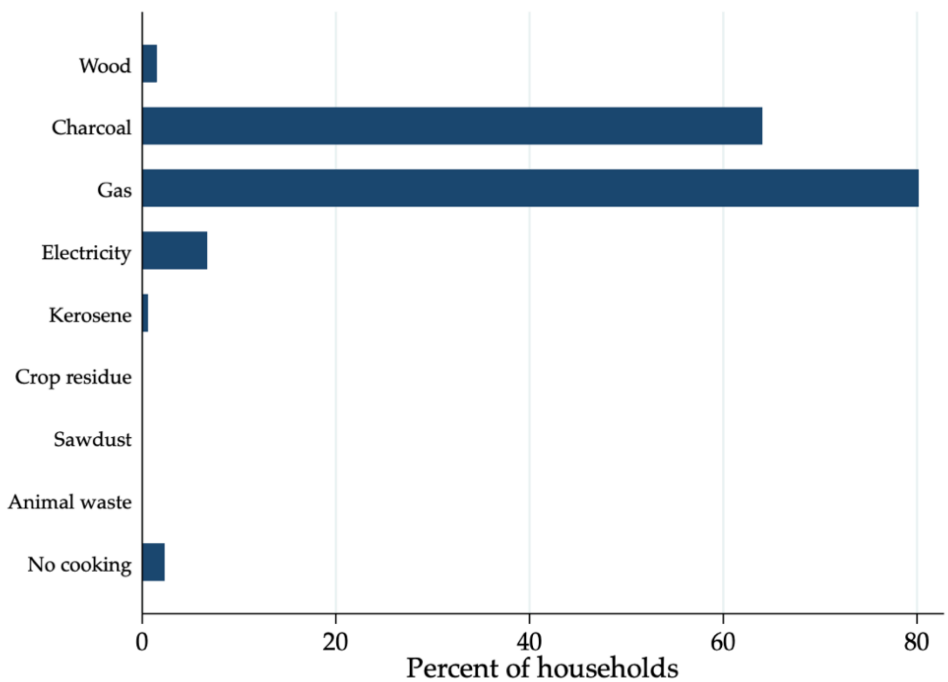
3.3.3 Household Outcomes

Summary:
1. *Cooking is a primary reason households use other energy sources besides electricity. While nearly all households (97.7%) cook at least some meals at home, only 6.7% of households use electricity for cooking.*
2. *The most commonly used cooking fuels are charcoal (64% of households) and gas (80.2%), and gas is the primary fuel for 70% of households.*
3. *Households primarily report not using electricity to cook because other fuels are cheaper (67% of households).*
4. *Nearly all households surveyed at baseline reported using an electric light bulb for lighting purposes, and CFL (50.4%) and LED (62.2%) are the most common types.*
5. *Households also report using cellphones (65.8%) and flashlights (32.9%) as alternative sources of light, primarily as backups to lightbulbs connected to electricity (the main lighting source for 87.9% of households).*
6. *Households report using light bulbs for light for 8.3 hours per day, compared to 1.7 hours for all other sources of light (on average).*
7. *Households use light to read or study for an average of 1.2 hours per day, with 90.8% of these studying hours using lightbulbs.*

Households may use electricity for a variety of purposes, including entertainment, studying, cooking, and home production. This section reports on household-specific activities that might be affected by changes in electricity: use of electricity and other fuels for cooking and use of lighting for reading or studying.

Cooking Energy Use

Figure 17. Use of Fuels for Cooking in the Last 3 Months



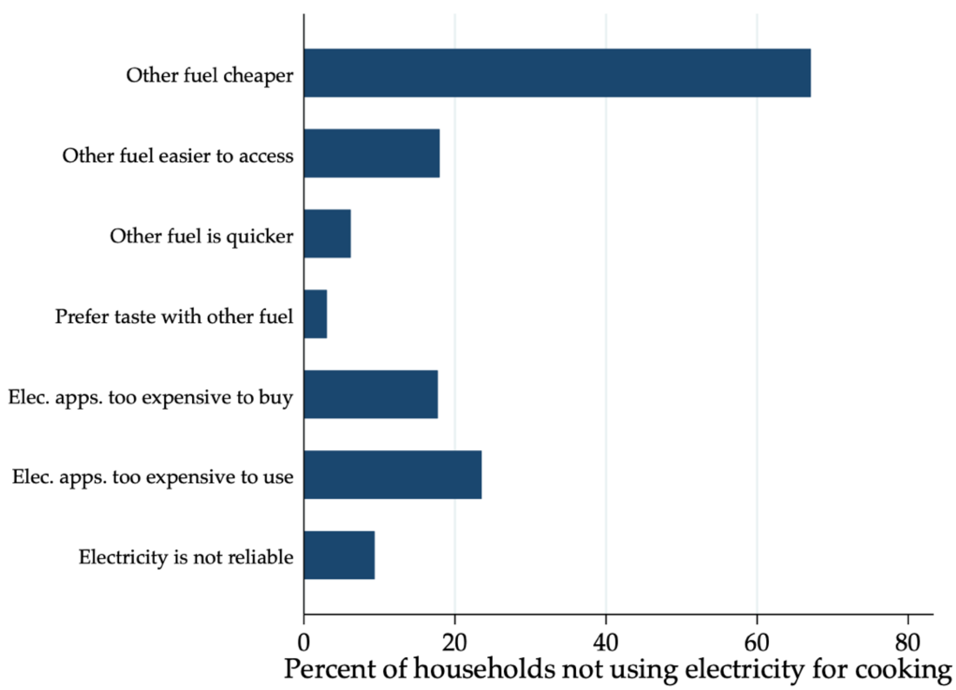
Source: Baseline survey.

We have shown above that households commonly use other fuels besides electricity, and that this is driven by the use of charcoal (64.0% of households) and gas (80.2%) for cooking. Figure 17 summarizes the share of households reporting use of different fuels for cooking in the past 3 months, and emphasizes the key role of these two fuels. Nearly all households (97.7%) cook at least some meals at home, and gas is the main fuel for cooking for 70% of households, followed by charcoal for 29.3%, with very small residual shares for wood, electricity, and kerosene.

Just 6.7% of households report using electricity for cooking in the past 3 months. Figure 18 below summarizes the reasons households give for never having used electricity for cooking. Among those that did not use electricity for cooking in the 3 months before the interview, the most common reason is that other cooking fuels are cheaper (67%). Costs of buying and using electric cooking appliances are also a barrier for a large share of households. Electricity reliability is not a major reason: it is mentioned by only 9% of households. Consequently, we do not expect that line bifurcation treatment will affect household use of fuels for cooking.

Though only 6.7% of households report using electricity for cooking in the 3 months before the survey, 15.5% of households report having ever used electricity for cooking. Seventy-five percent of households that used electricity cooking outside the 3 months before the survey had used it in 2020 or 2021. This indicates that a higher share of households might report using electricity for cooking when asked about a longer time frame. The reasons households give for not currently using electricity for cooking after having previously done so are similar to those given by households that have never used electricity. An additional reason, given by 10.7% of those previously using electricity to cook but not in the past 3 months, is that one of their electric cooking appliances is broken.

Figure 18. Reasons Households Report Never Having Used Electricity for Cooking



Source: Baseline survey.

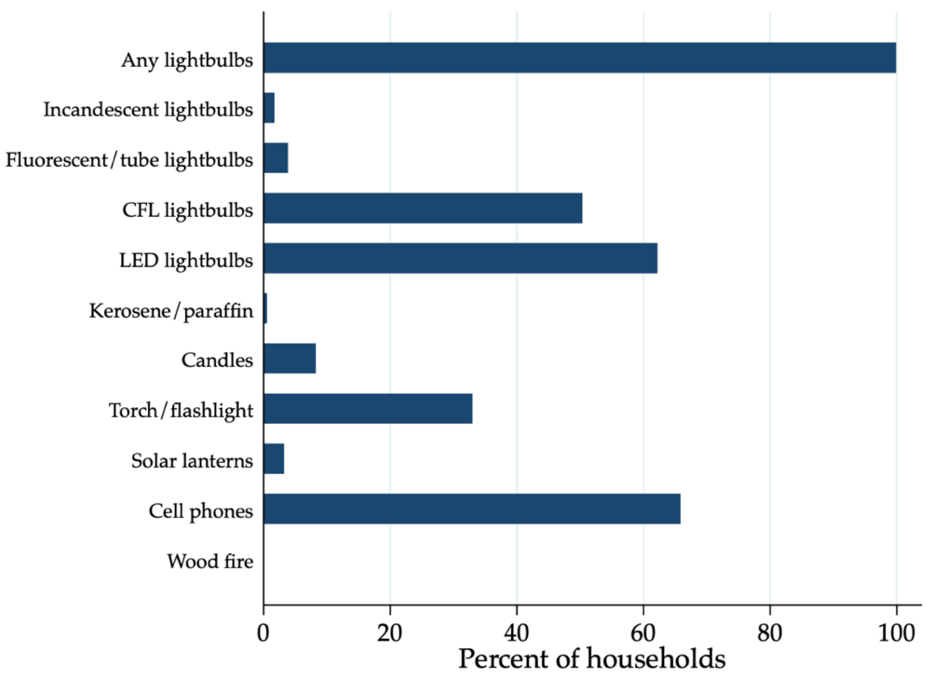
Although few households report using electricity for cooking, a larger share report owning some form of kitchen appliance. Electric kettles are owned by 25.6% of households but may not have been considered by respondents when discussing cooking since heating water with a kettle may be thought of as distinct from cooking/meal preparation. Similarly, 17.1% of households reporting owning a microwave but may not consider using a microwave as “cooking.” But 13.7% of households own a rice cooker, which would presumably be thought of as used for cooking. On the other hand, just 1.3% of households own an electric stove and 0.7% own a halogen oven, the types of appliances most households would consider as central for cooking.

Overall, 25.9% of households report owning an electric kitchen cooking appliance other than a kettle. Among households with such an appliance, 22.0% used electricity for cooking in the last 3 months and 44.3% ever used electricity for cooking. This might reflect household reports that not all cooking appliances are working and concerns around costs of cooking with electricity. But it may also suggest that some households are not considering some types of uses of electric kitchen appliances as "cooking." The endline survey will include an additional question explicitly asking households whether they have used any of the above electric kitchen appliances, to better measure use of electricity for cooking, broadly construed.

As gas and charcoal play such a central role in household cooking, and electricity reliability is not a major reason households give for not using electricity to cook, we do not expect that use of gas and charcoal or spending on these fuels will fall in treatment households relative to control households. However, it is possible that improved reliability in line bifurcation treatment sites could encourage some households to begin using electricity more for cooking and we may be able to detect this by the end of the exposure period.

Lighting Energy Use

Figure 19. Households Sources of Lighting in the Past 3 Months



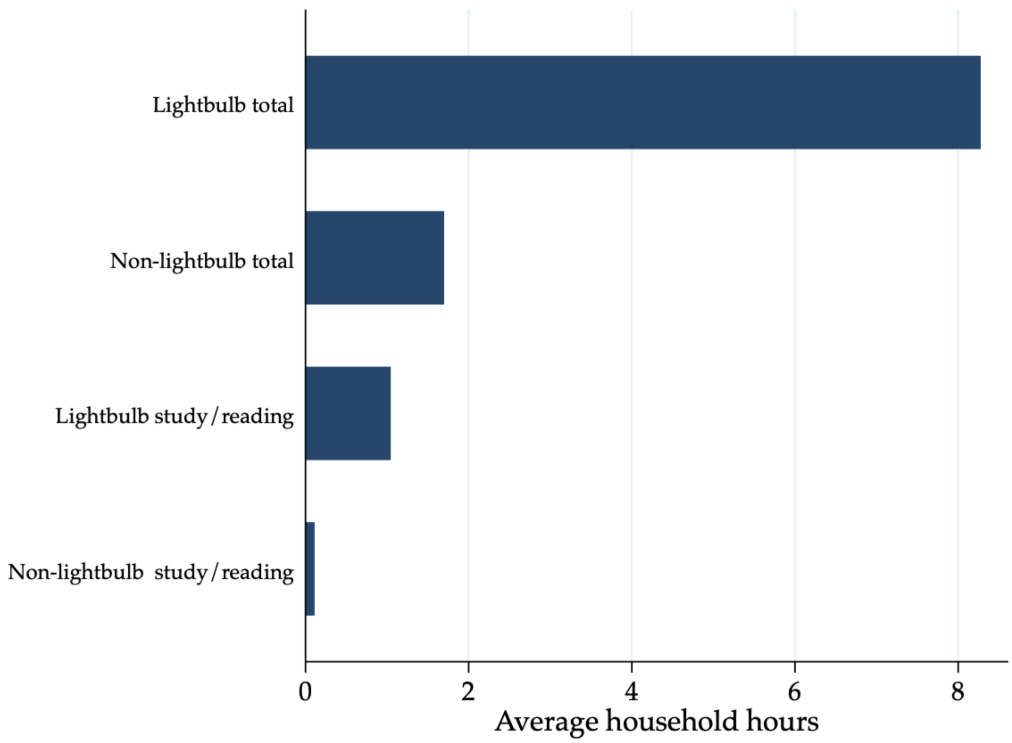
Source: Baseline survey.

Another area where changes in power reliability might have particular effects on households is the use of electric lighting for studying. Electric light bulbs are used by nearly all households in the baseline survey. Figure 19 summarizes the share of households using different kinds of light bulbs for lighting, along with the share using different sources of light at any time in the past 3 months. Most households use just one type of lightbulb, and CFLs (50.4% of households) and LED (62.2%) lightbulbs are the most used lighting technologies.

Households report using a few other sources of light over the 3 months prior to the interview. Cell phones are the most commonly used alternative to lightbulbs (65.8% of households), with flashlights (32.9%) and candles (8.2%) somewhat less common. All of these alternate sources of light are primarily used as backups to lightbulbs connected to electricity, which is the main source of lighting for 87.9% of households.

Figure 20 summarizes the average hours per day households use different light sources. On average over the past 3 months, households report using light bulbs for light for 8.3 hours per day, compared to 1.7 hours for all other sources of light. The baseline survey also includes questions on the use of lighting for household members when reading or studying. Households report using light to study for an average of 1.2 hours per day, with 90.8% of these studying hours using lightbulbs. The results are similar when considering just households with school-age children.

Figure 20. Average Household Hours per Day of Light Used in the Past 3 Months



Source: Baseline survey.
Note: The survey asks "*On average, how many of [the total hours per day light bulbs are used] in total did you or someone in your household use this type of lightbulb for reading or studying (for school/university/courses)?"* Lightbulb use for study/reading therefore focuses on uses to school-related purposes, but is asked for all households regardless of the presence of school-age children.

We hypothesize that the share of households reporting sources of light other than lightbulbs as their main source of lighting will decrease in treatment sites relative to control sites by the end of the exposure period, as more reliable electricity for treatment households should allow them to use lightbulbs whenever they prefer. As a result, we would expect the ratio of hours of light from lightbulbs compared to other sources would increase in treatment sites. Treatment households might also increase their hours spent using light from bulbs to study or read, with greater availability of electricity for lighting. Finally, if treatment households perceive reductions in voltage fluctuations and thus in the risk that bulbs will burn out, we might also see an increase in ownership of LED lightbulbs relative to CFL and other lightbulbs, given their advantages in lifespan, energy efficiency, and brightness.

3.4 Evaluation Question 3

What happens within households and businesses when the power goes out? When it comes back on?

This evaluation question addresses the very short-run impacts of electricity outages and decisions that customers make in response to poor power reliability. Answering this question will shed light on the costs to households and business of unreliable electricity, both in terms of using alternatives to electricity and in terms of impacts on household well-being and business activities.

This baseline report presents descriptive statistics for the survey sample on use of alternative energy when the power goes out, impacts of unreliable electricity on businesses and households, and willingness to pay for more reliable electricity. Sub-section 3.4.1 discusses customers' use of alternative energy when the power goes out, looking specifically at generator use and use of different sources of light and building on results presented in section 3.3. Sub-section 3.4.2 presents results on the temporary and permanent coping mechanisms that businesses turn to in response to unreliable power, and on estimates of revenue lost due to poor reliability. Sub-section 3.4.3 considers how power outages affect households in terms of loss of perishable goods, health issues, and changes to cooking practices. Finally, sub-section 3.4.4 discusses how much households and businesses would be willing to pay for different scenarios of improved electricity reliability and for a generator, as an indicator of the costs to customers of poor reliability.

The endline survey will estimate changes by treatment status in use of generators and alternative lighting, in business coping mechanisms and estimated revenue losses, in household losses of perishables in health risks, and in willingness to pay for improved reliability. At the end of the exposure period, assuming that the LB investments improve power reliability, we hypothesize a reduction in these measures associated with costs of unreliable power for households and businesses in treatment sites relative to those in control sites.

3.4.1 Alternative Energy Use During Outages

***Summary**:*

1. *Few businesses (5.2%) and households (2.6%) have a generator – most go without electricity during power outages.*
2. *Costs may be a barrier to investment in generators: the median customer spent 1.5 years' worth of electricity spending to acquire their generator.*
3. *Most customers with a generator use it only a few times pe year. Just 14 of 52 (26.9%) of businesses with a generator and 4 of 25 (16.0%) of households say that they always use a generator when there is a power outage.*
4. *The decision to turn on a generator during an outage involves many factors. Use is generally reserved for situations with greater need for electricity. Costs of operating a generator are a concern.*
5. *Generator use and associated costs may fall in treatment sites relative to control sites, but only if a significant share of outages are in the LV network rather than the MV network.*
6. *Most households (88%) and businesses (89%) report that lightbulbs were their primary source of light over the prior three months.*
7. *Cell phones are the most common backup to lightbulbs during power outages (around half of respondents). Flashlights are also common (around one quarter of respondents).*
8. *Surprisingly, 24% of businesses and 9% of households most commonly use no backup sources of lighting during outages, perhaps because these occur during the day.*

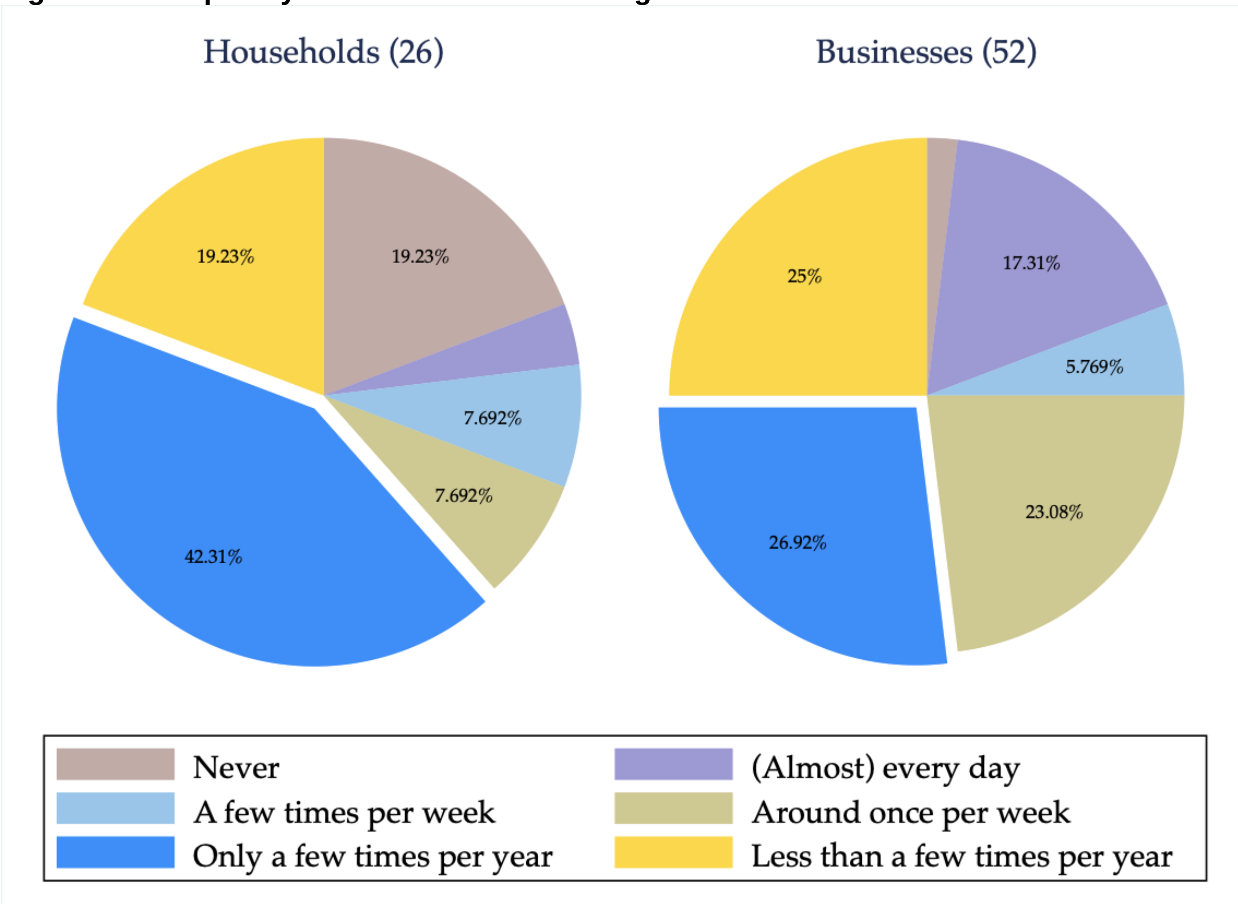
Generator Use

A primary hypothesized mechanisms by which customers can cope with power outages is to use a generator as a backup source of electricity. As discussed in Section 3.3, however, generator ownership is quite low: just 52 of 1,004 businesses (5.2%) and 26 of 998 households (2.6%) have a generator. Ownership of other possible backups to grid power such as solar panels and wet cell batteries is less than one percent. The implication is that the vast majority of customers do not have any access to electricity during grid power outages.

The median customer with a generator spent GHS 1,500 (USD 232) to acquire it—around 1.5 years of electricity spending at current levels. These are therefore significant investments, and may not be considered worthwhile by some customers at current levels of power reliability. Section 3.4.4 discusses evidence on how much customers would be willing to pay for a generator in.

Among those that do have a generator, the generator should serve as a valuable source of backup power. Yet, just 59.6% of businesses and 23.1% of households with a generator report using it in the past 3 months. Most customers report using it just a few times per year, with business using generators slightly more frequently than households on average (Figure 21). This implies that customers are typically not turning on their generators during outages. Indeed, just 14 of 52 (26.9%) of businesses with a generator and 4 of 25 (16.0%) of households say that they always use a generator when there is a power outage, and 38.5% of such businesses and 42.0% of households report rarely or never using their generator.

Figure 21. Frequency of Generator Use Among Generator Owners

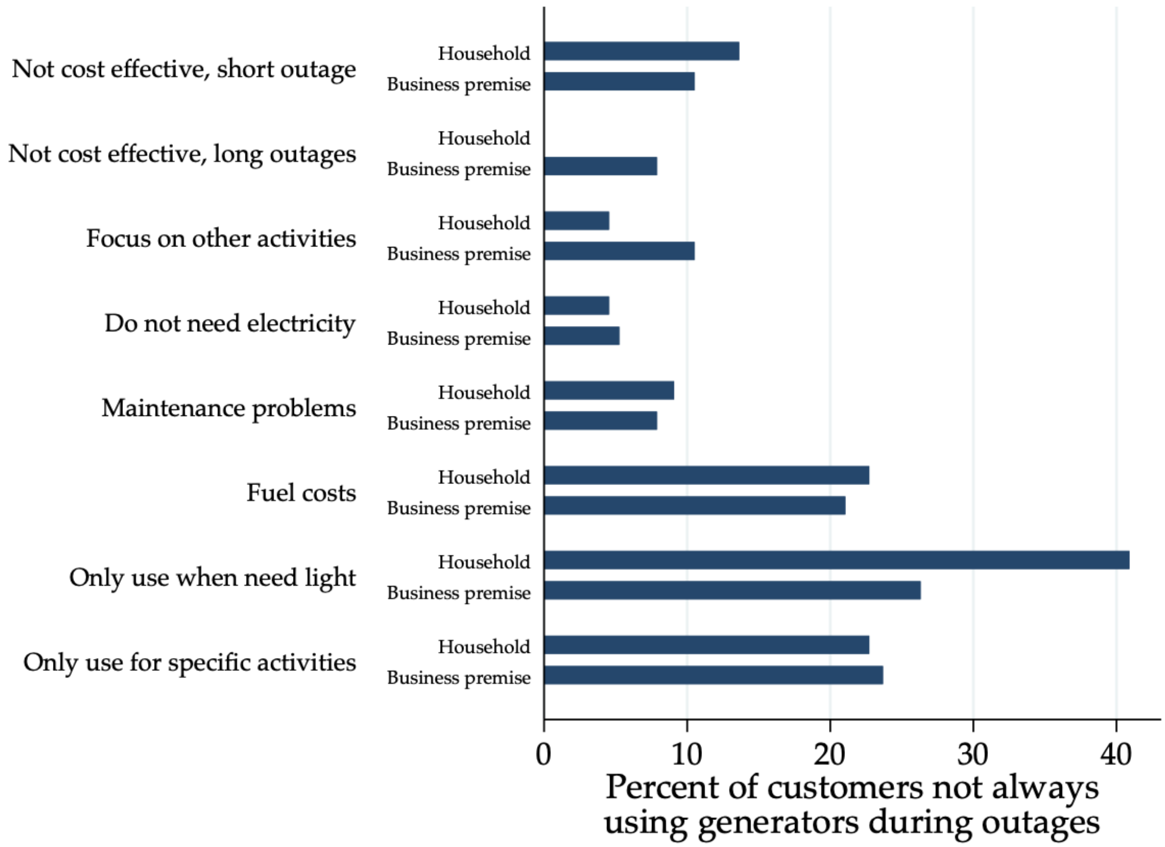


Source: Baseline survey.

This could be because current outages are not severe enough to justify generator use. Nearly one-quarter of generators owned in the sample were acquired in 2015, the peak of the Dumsor crisis period, and 43.6% were acquired at some point during this crisis from 2012-2016. Customers may have purchased generators when there was a higher need, and now store them in case of future electricity load shedding, rather than using them regularly for current shorter and irregular outages.

We asked all generator owners that do not always use their generator during outages to indicate their reasons for this decision. The percentages of households and businesses giving different reasons are presented in Figure 22. Reasons are fairly similar across households and businesses, though households are more likely to say that they only use a generator when they need light, indicating they would not use a generator during the day. This is the most common reason customers give for not using a generator, reported by 41% of households and 26% of businesses. A related reason, given by 23% of these respondents, is that they only use a generator for specific activities, meaning they would not turn it on if an outage did not disrupt one of these activities. Similarly, 8% of respondents say they do not use a generator because they can focus on other activities, and 5% say they do not need electricity. Taken together, these responses illustrate that the decision to turn on a generator during an outage involves many factors, and that use is generally reserved for situations with greater need for electricity.

Figure 22. Reasons Customers Report Not Using Their Generator During Outages



Source: Baseline survey.

The decision to use a generator is also complicated by fuel costs, cited by 22% of these customers, and maintenance issues, cited by 8%. Twelve percent of these customers report not always using a generator during outages because it is not cost effect for short outages; another 5% report that it is not cost-effective even for long outages. The relatively low share of respondents giving these reasons indicate that while costs of running a generator (conditional on having one) are a constraint for some, it is not the primary concern.

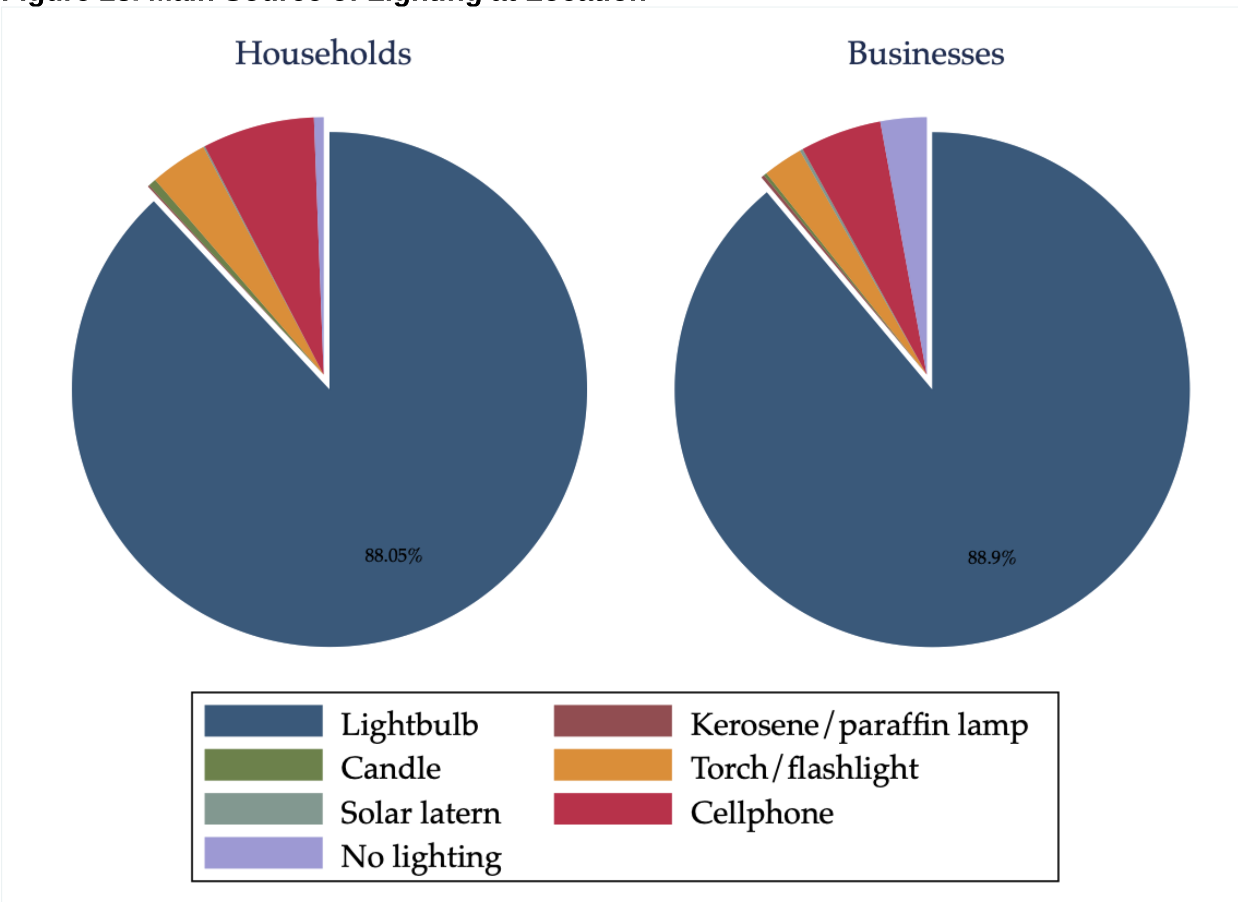
Due to relatively low use of generators, mean monthly spending is low. Among the 37 businesses and households using their generator in the past 3 months, the median monthly spending on fuel and maintenance is GHS 43 (~USD 7), 21.5% of their spending on electricity.

Based on the low levels of generator use, identifying any differences by LB treatment status at endline may be challenging. Electricity use and associated costs may fall in treatment sites relative to control sites as the need to deal with power outages falls. This would only be the case, however, if a significant share of outages is in the LV network rather than the MV network, as LB improvements do not address causes of outages at the MV level.

Back-up Lighting Sources

Most households (88%) and businesses (89%) report that lightbulbs were their primary source of light over the prior three months (Figure 23). The next most common is cell phones, reported as the main source of lighting 7% of households and for 5% of businesses, suggesting these respondents were either not using very much lighting or faced some issues with their lightbulbs or electricity connections, as nearly all report having lightbulbs. Though lightbulbs are the primary light sources for nearly everyone, 33% of households report using flashlights at least once in the past 3 months along with 66% using cell phones, compared to 25% and 50% of businesses, respectively. These sources are used primarily as backups to lightbulbs.

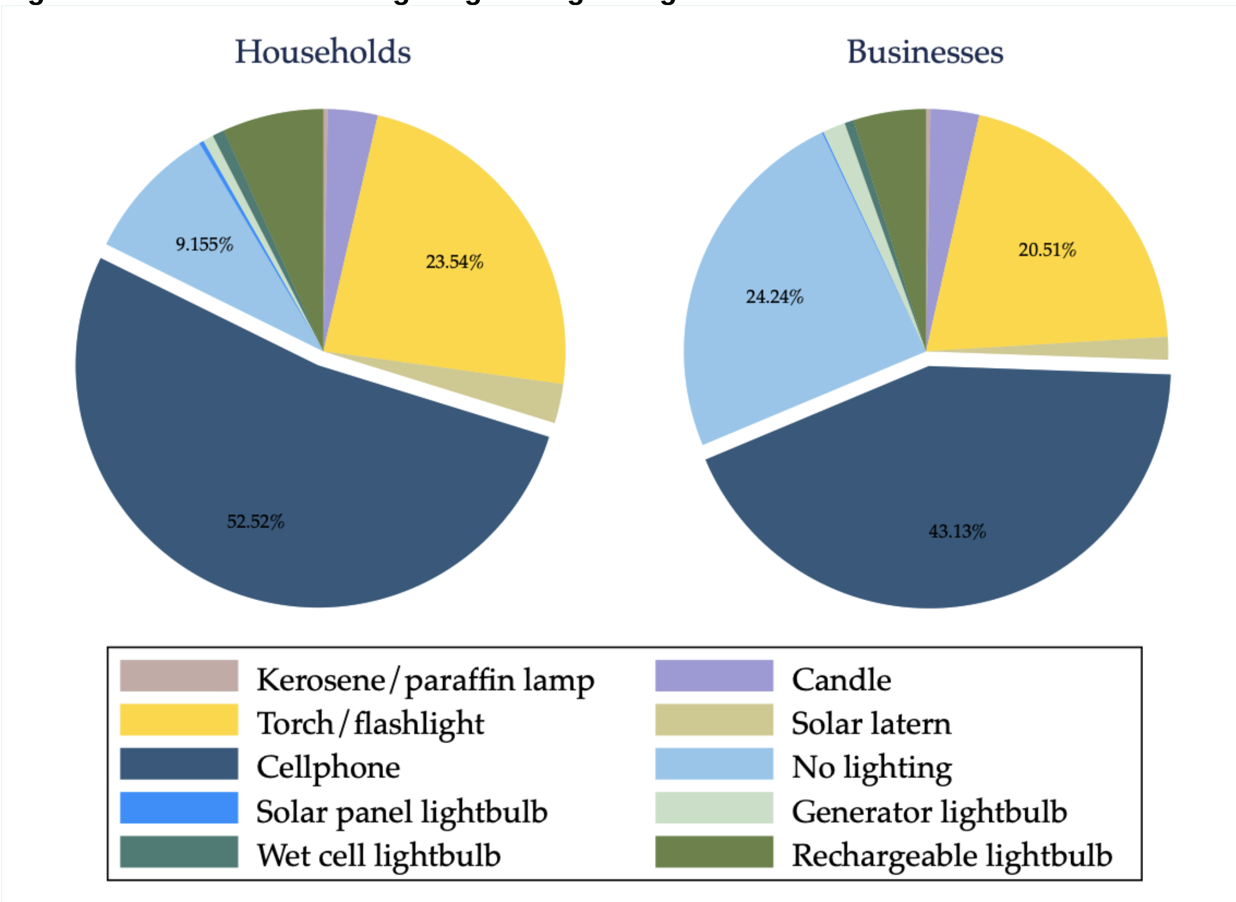
Figure 23. Main Source of Lighting at Location



Source: Baseline survey.

The use of electric lightbulbs for light indicates households and businesses need backup light sources during outages. Figure 24 summarizes the main source of lighting that respondents report using when the power is out. For both households (53%) and businesses (43%) cell phones are the most common, reflecting the ubiquity of phones and the ease of using them as a temporary light source. Flashlights are also common (24% of households and 21% of businesses), and some respondents (7% of households and 5% of businesses) also report using rechargeable lightbulbs, which can store some power to keep providing light during a power outage.

Figure 24. Main Source of Lighting During Outages



Source: Baseline survey.

Surprisingly, a relatively large share of respondents indicate that they most commonly use no backup sources of lighting during outages. This is more common for businesses (24%) than households (9%). This may be because many outages occur during the day when no light sources are needed. This would be more likely for businesses, primarily open during daylight hours, than for households which occupy their premises at all hours. The endline survey may include a follow-up question on this topic to probe this response further.

We hypothesize that improved electricity reliability will increase the prevalence of lightbulbs as the primary light source in treatment relative to control areas. As outages may still occur for a variety of reasons, we do not expect any changes in the use of backup light sources.

3.4.2 Impacts of Poor Electricity Reliability on Businesses

***Summary**:*
1. *On average, sample businesses report that electricity is a very important obstacle to business activities, despite most of them being small with few electric appliances.*
2. *Over one-quarter of businesses stopped business activities in the past month due to unreliable electricity.*
3. *The median business reports that revenues in the past month would have been 16% (USD 31) higher if they had perfectly reliable electricity.*
4. *The biggest obstacles to businesses from electricity are the unpredictability of outages and the costs of electricity. Outage length and frequency and voltage fluctuations are also important obstacles.*
5. *Some businesses can switch tools or activities in response to outages, but stopping work is the most common temporary response to power outages. Few businesses use alternative energy, though some report purchasing a generator or other alternative energy source in the past year.*

The baseline survey includes questions asking businesses about the challenges they face due to unreliable electricity, and the various ways they might respond to power outages or other reliability issues.

Table 10 presents summary statistics for outcomes reflecting the challenges businesses face. One a scale from 1 (not at all important) to 5 (extremely important), the mean is 3.87, reflecting that the median business reports that electricity is a very important obstacle to business activities. This indicates that even for very small businesses, with just a few electric appliances and in sectors not necessarily reliant on electricity, reliability is an important constraint on their activities. While most businesses report not having to stop business due to poor reliability in the past month, over 25% report having to stop business for at least one day, including 11 businesses that were not able to operate for over one-third of days in the past month. Similarly, most businesses were able to stay open for all of their regular hours in the past month, but 25% report closing for over 5% of business hours, including 10% of businesses closing for over a quarter of their business hours.

Table 10. Summary Statistics for Outcomes Related to Reliability Challenges, Businesses

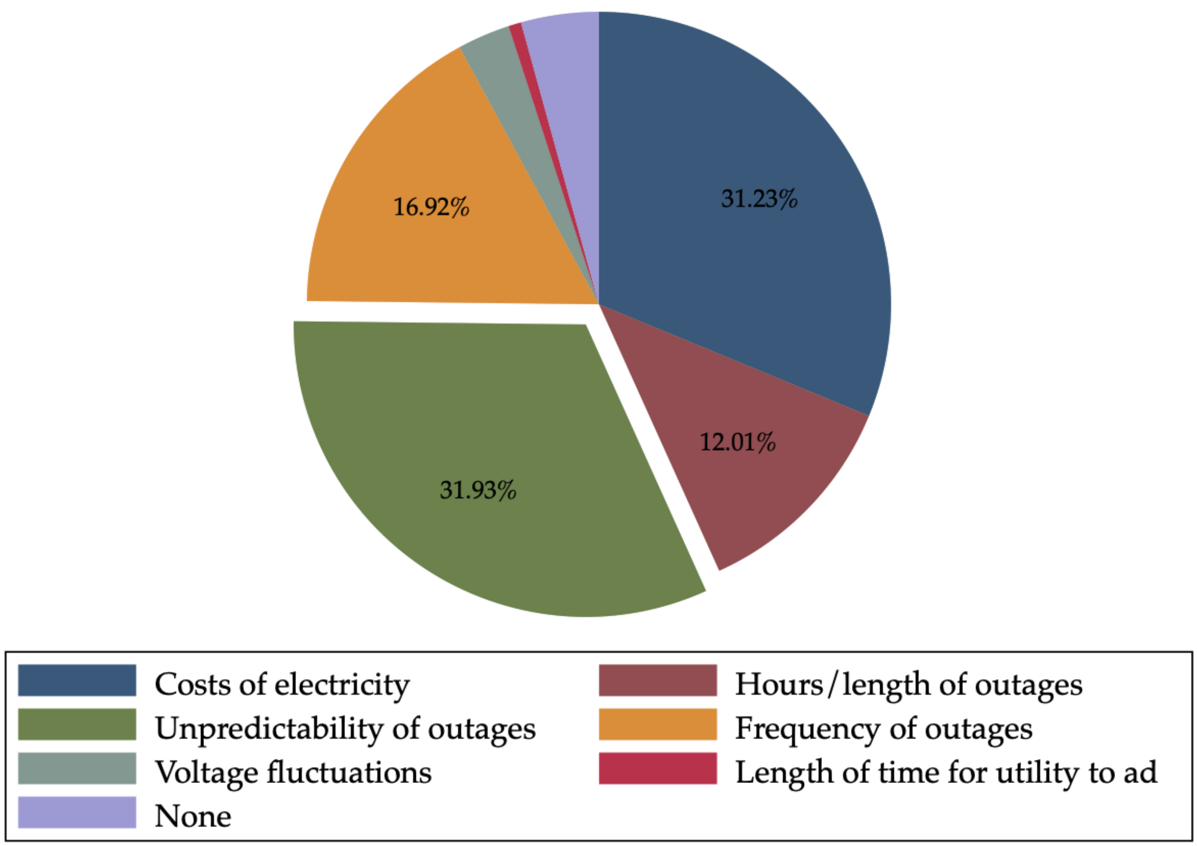
	N	*Mean*	*SD*	*Min*	*25th*	*50th*	*75th*	*Max*
Electricity challenges								
Importance of electricity as obstacle (1-5)	1004	3.87	0.99	1	3	4	5	5
Days in past month stopped business due to reliability	1004	0.90	2.35	0	0	0	1	30
Percent of business hours in past month stopped due to reliability	1004	7.34	17.67	0	0	0	5	100
Estimated revenues								
Total revenue in past month (GHS)	870	3,462.00	21,183.76	0	600	1,200	3,000	600,000
Total revenue if perfect reliability (GHS)	790	4,370.58	36,056.24	0	800	1,500	3,000	1,000,000
Difference in revenues if perfect reliability (GHS)	786	999.78	14,331.54	0	0	200	500	400,000

Source: Baseline survey. GHS 100 ≈ USD 16 at the time of surveying.

We also ask businesses to estimate what their revenue in the past 30 days would have been with perfect electricity reliability. Among businesses that reported an estimate of both their actual revenue and their expected revenue under perfect reliability, the mean difference is GHS 1000 (~USD 153), and the median is GHS 200 (~USD 31). This is a sizeable difference, representing one-sixth of actual business revenues. Over two-thirds of businesses believe that their revenues would have been higher with perfect electricity reliability. This suggests businesses should be willing to pay a significant amount on average to access perfectly reliable electricity, which section 3.4.4 discusses in more detail.

Figure 25 illustrates what businesses report as the main obstacle to businesses from their electricity provision. The two most common obstacles are the unpredictability of outages (32% of businesses) and the cost of electricity (31%). The frequency (17%) and length (12%) of outages are also commonly cited. This suggests that if businesses could improve one aspect of electricity reliability (holding other aspects constant), they would favor being able to know when outages will occur. Of course, this will not always be possible, but given low levels of overall outage awareness, any efforts by ECG to disseminate information about planned outages will be valuable for customers.

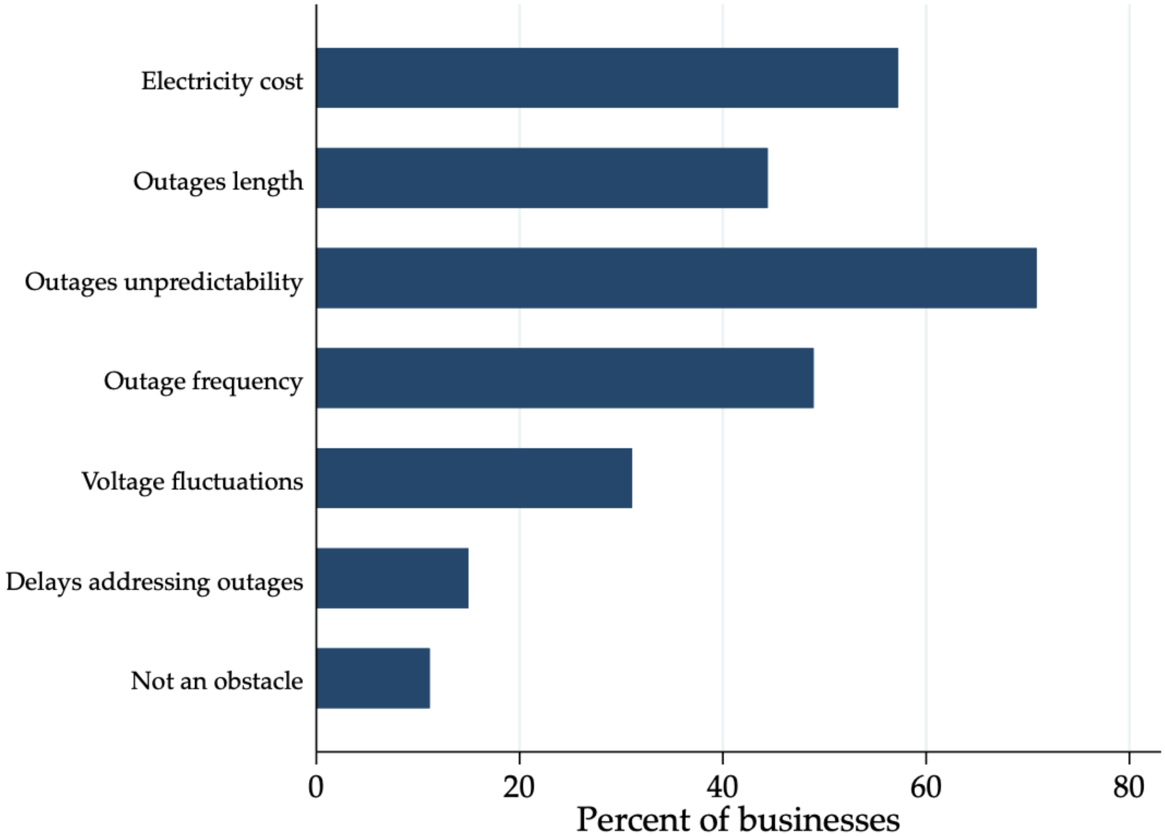
Figure 25. Main Obstacle to Businesses from Electricity Provision



Source: Baseline survey.

Businesses could report multiple aspects of poor reliability as obstacles in addition to the primary obstacle (Figure 26). The relative shares of businesses reporting different obstacles is similar to the shares reporting which obstacles are their primary concerns. Seventy-one percent report that unpredictability of outages is an obstacle for businesses, followed by 57% reporting electricity costs, 49% reporting outage frequency, and 44% reporting outage length. Thirty-one percent of businesses report that voltage fluctuations are an obstacle.

Figure 26. Percent of Businesses Reporting Particular Obstacles Due to Poor Reliability

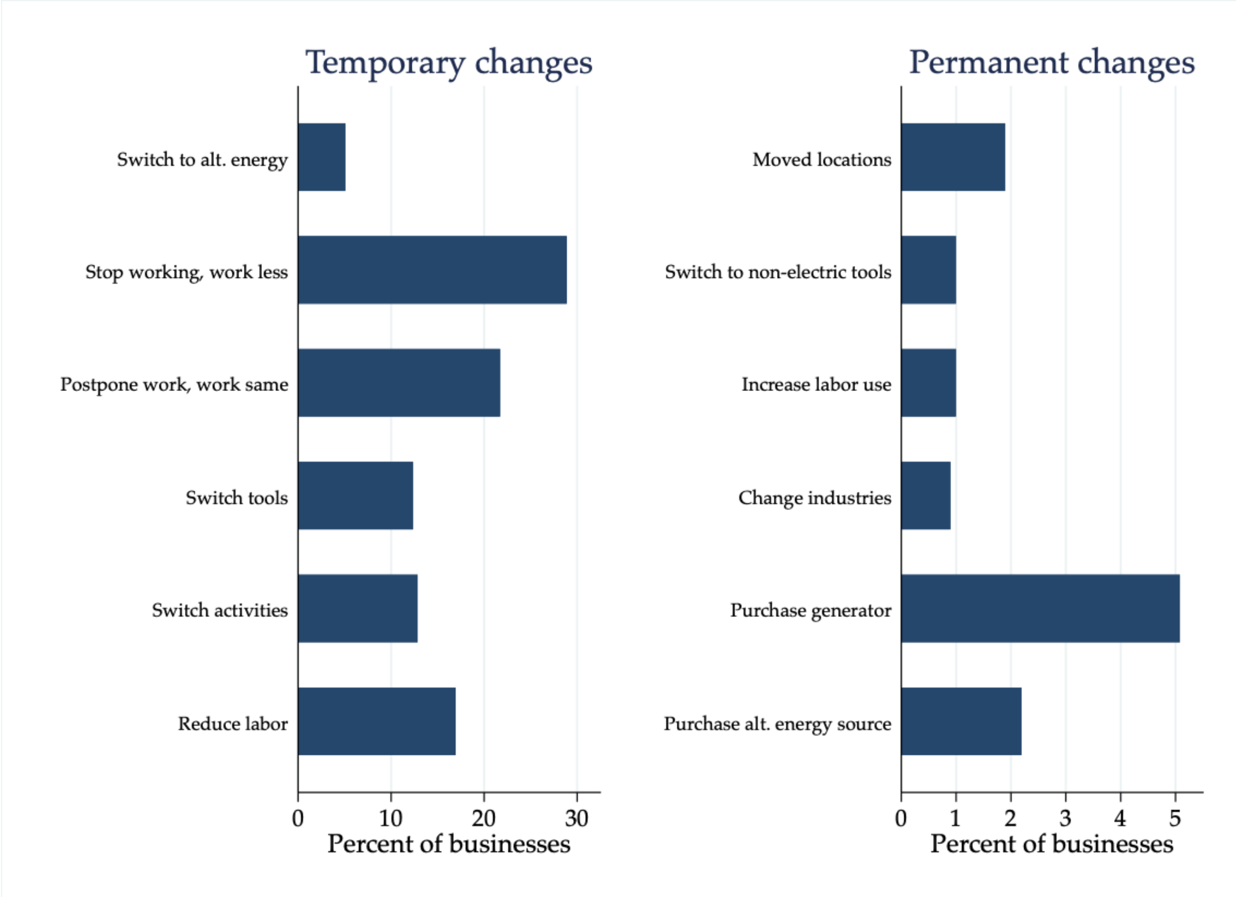


Source: Baseline survey.

Businesses may respond to electricity disruptions in a variety of ways. Figure 27 examines temporary and permanent changes to activities that businesses had made in the past year in response to unreliable electricity. Consistent with low ownership of generators, just 5% of businesses report temporarily switching to an alternative energy source, while 5% report have purchased a generator in the past year as a permanent response to reliability issues. The most common temporary responses are to stop working, with 29% of businesses reducing work hours as a result while 22% shift their work hours but work the same amount, and 17% reduce their amount of labor. Some businesses switch their activities (13%) or tools (12%) to be able to continue working in some way while the power is out. Businesses thus demonstrate some ability to adapt in response to unreliable power, but for many these adaptations involve working—and thus earning—less.

Few businesses report making any permanent changes in response to reliability issues in the past year, besides purchasing a generator. Twenty-two businesses (2.1%) purchased another alternative energy source (solar panels or wet cell battery). Nineteen business (1.9%) report having moved to a new location in order to escape particularly unreliable electricity. Less than one percent of businesses report switching to permanently using more non-electric tools, to permanently using more labor rather than electric appliances, or changing industries.

Figure 27. Percent of Businesses Changing Activities in Response to Poor Reliability



Source: Baseline survey.

Since a primary objective of LB construction is to reduce loads on parts of the electricity grid, voltage should become more regular in LB treatment sites. We would thus expect to see fewer businesses concerned about voltage fluctuations in treatment sites relative to control sites, and more generally for treatment businesses to report that reliability is less of an obstacle to business. Unless LB construction also meaningfully reduces outages in treatment sites relative to control sites, we would not expect to observe any changes in other attitudes towards electricity reliability or in business responses. But to the extent that LB treatment does reduce voltage fluctuations and improves electricity reliability more generally, we would expect revenues to rise in treatment sites relative to control sites, and for the gap between actual revenues and expected revenues under perfect reliability to fall.

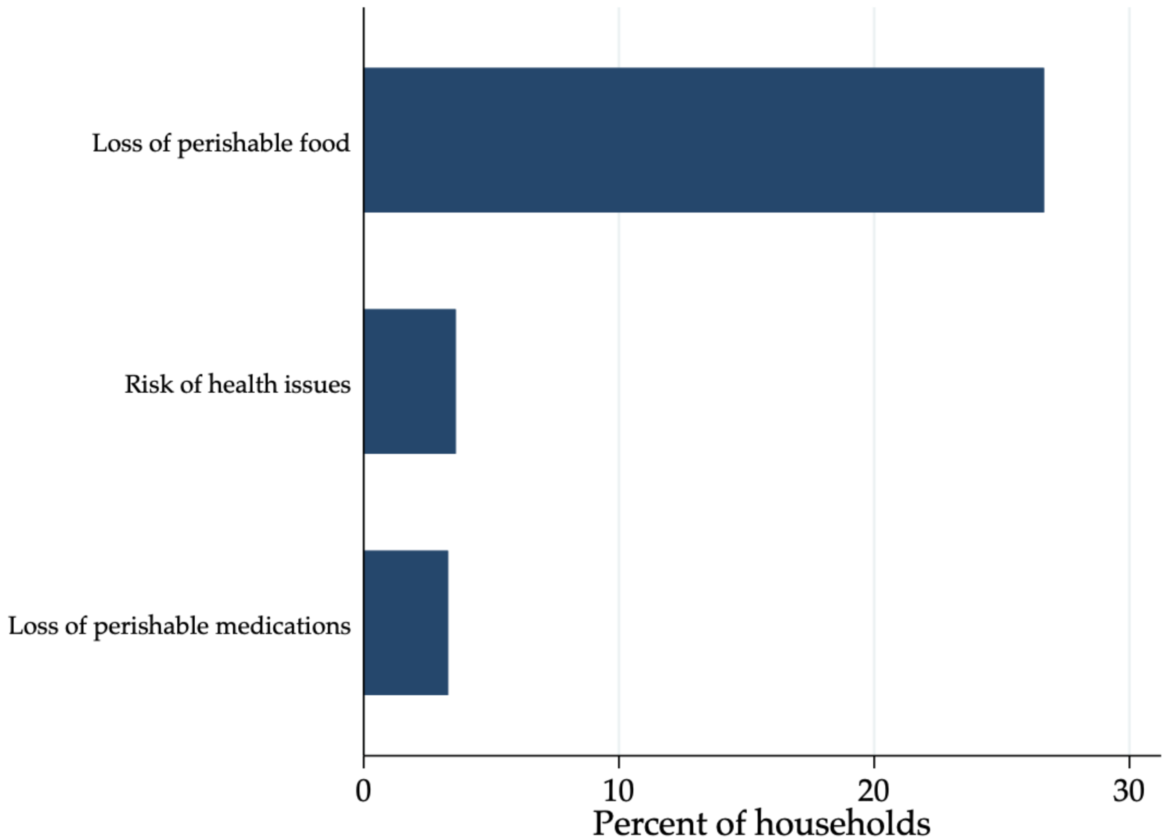
3.4.3 Impacts of Poor Electricity Reliability on Households

***Summary**:*

1. *Households use electricity in a variety of ways, making it challenging to measure how unreliable electricity affects them outside of their energy use and spending.*
2. *Loss of perishable food (27% of households) and medicines (3%) due to unreliable electricity are important observable challenges for households.*
3. *Electricity outages do not appear to create difficulties for cooking, as electricity is not a primary cooking fuel for most households.*

Households may experience a variety of impacts of unreliable electricity due to the diversity of ways in which they consume electricity. Figure 28 presents three observable ways that poor reliability might reduce household well-being. Twenty-seven percent report having to discard perishable food due to reliability issues, reflecting how reliable power is important for running refrigerators to keep food fresh. The same issue applies for some medicines, with 3% of households reporting losing perishable medications due to unreliable power. Three percent of households also report having faced increased risk of health issues, which may be due to loss of power for specialized health equipment, heat exposure, or other reasons.

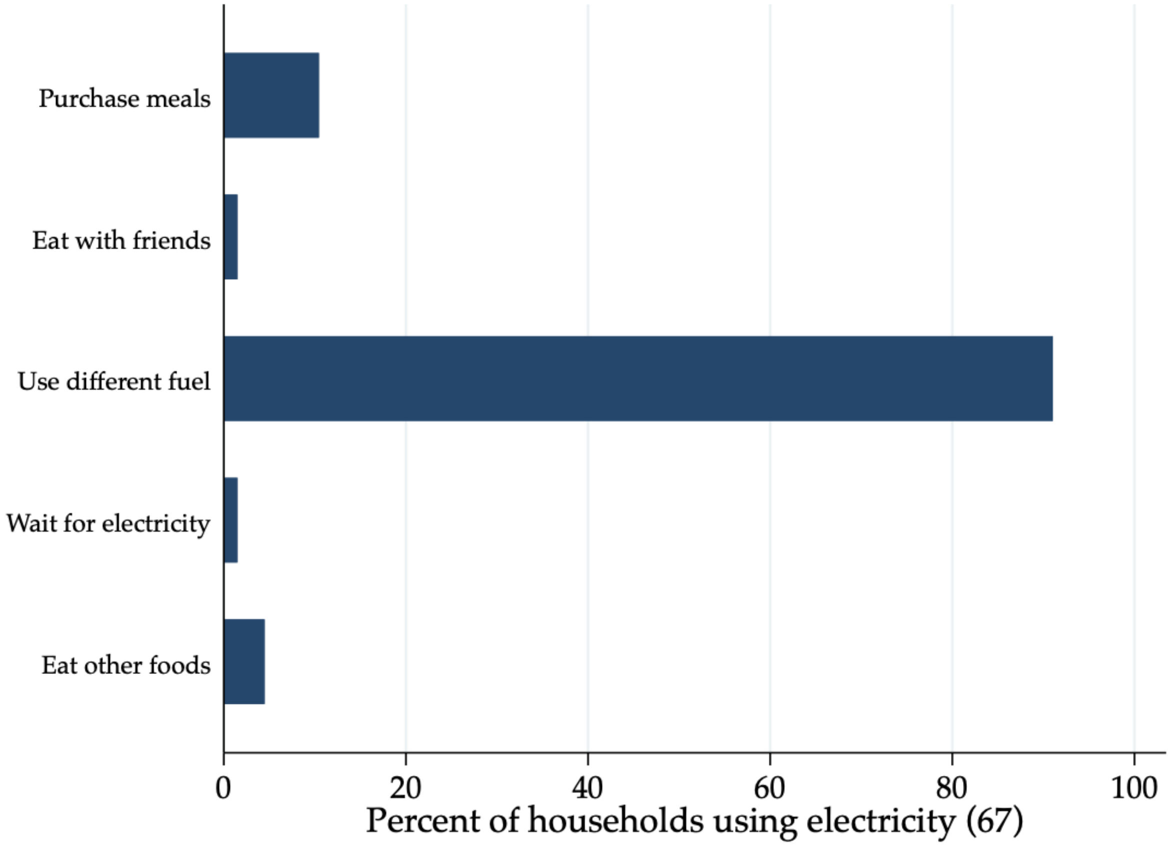
Figure 28. Percent of Households Reporting Particular Impacts of Poor Reliability



Source: Baseline survey.

Section 3.3.3 reports that just 6.7% of households report using electricity for cooking in the past 3 months. Among these households, when the power is out, most respondents (91%) report using other fuels to cook, consistent with electricity not being a primary fuel for most households (Figure 29). Ten percent purchase meals rather than cooking and 4% eat other foods that do not require cooking.

Figure 29. Responses to Outages Among Households Using Electricity for Cooking



Source: Baseline survey.

In terms of observed impacts on households, the main benefit of LB construction in treatment sites may be to increase the reliability of refrigerators so that households don't have to discard perishable food and medicine.

3.4.4 Willingness to Pay for Improved Electricity Reliability

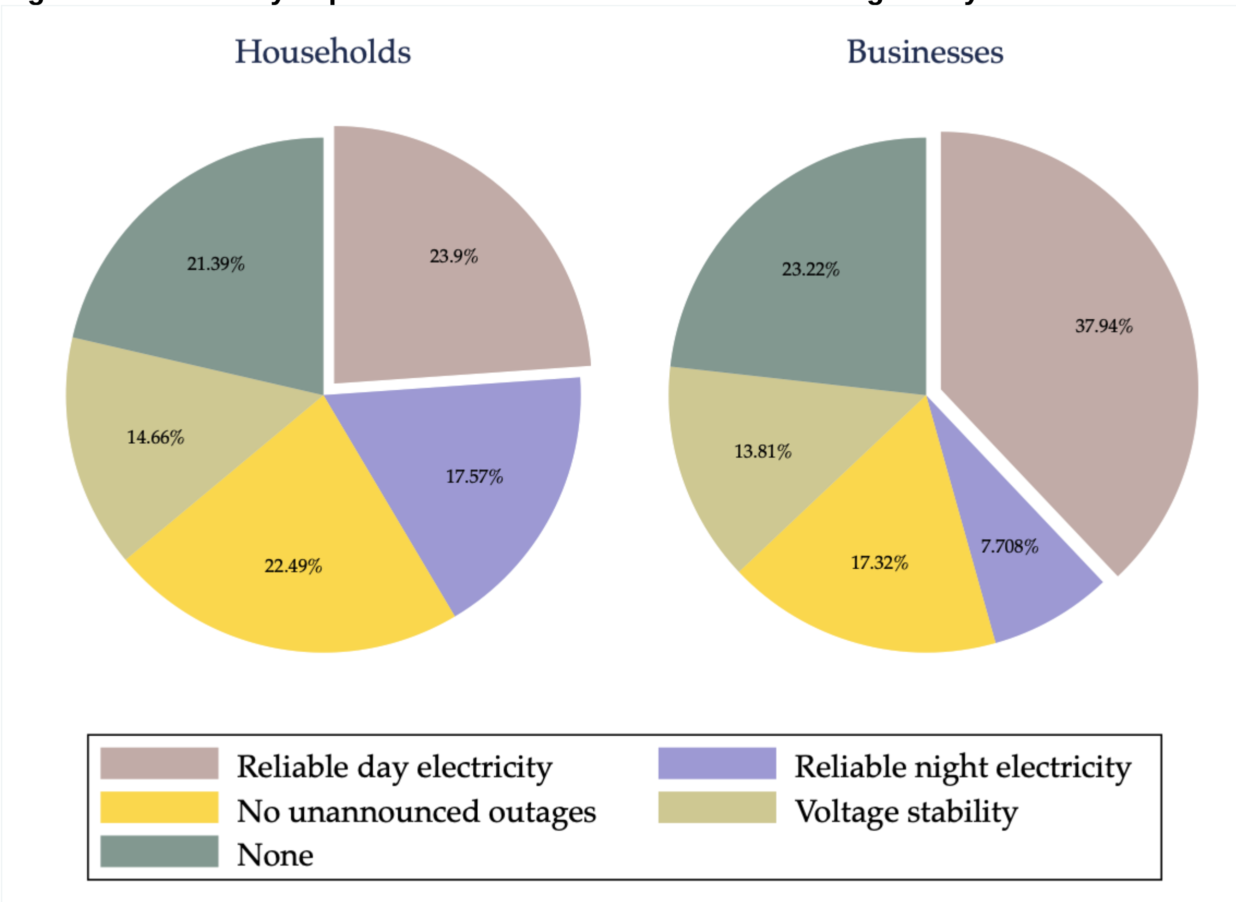
***Summary**:*

1. *We elicit respondents' willingness to pay (WTP) for different scenarios of improved electricity reliability and for a generator, as indicators of the cost of or reduced welfare from poor reliability.*
2. *Around one-third of both households and businesses are not willing to pay anything for perfectly reliable electricity. Costs are a constraint for many respondents.*
3. *The median respondent is willing to pay around 15% of their monthly electricity spending to ensure perfect reliability. But a subset of respondents indicate being willing to pay much more.*
4. *Households and businesses are willing to pay more to avoid outages than voltage fluctuations. Households appear to care less about the nature of the outages than about the total duration of outages. Businesses, however, would pay more to avoid a long unannounced outage than a long announced outage, and prefer 4 shorter outages to one longer outage with the same total duration.*
5. *Median WTP for a generator is USD 137 for households and USD 198 for businesses, with 10% of each not being willing to pay anything for a generator. This suggests more households and businesses than we observe should have a generator given the costs of available generators in Accra, but may be an over-estimate of WTP for a generator due to how the hypothetical scenario was framed.*
6. *Respondents in LB treatment sites have lower WTP for perfect reliability than those in control sites after controlling for other characteristics, despite similar reliability at baseline.*

To the extent that poor electricity reliability increases costs for businesses and households and decreases their revenues and well-being, respectively, they should be willing to pay for more reliable electricity. The baseline survey includes modules that aim to elicit respondents' willingness to pay (WTP) for various scenarios of improved electricity and for a generator. The amounts that respondents are willing to pay can be seen as estimates of the value they place on the costs they face and on their lost revenue/well-being, which might otherwise be difficult to measure, particularly for households.

We first ask respondents what aspect of electricity service they would be willing to pay the most to improve (Figure 30). Unsurprisingly, the most common response for households (24%) and businesses (38%) is more reliable electricity during the day, with the difference in shares for households versus businesses likely reflecting that businesses consume more electricity during the day relative to households. The next area respondents would be willing to pay the most for, above reliable electricity at night, is to eliminate unannounced outages (22% of households and 17% of businesses). Importantly for the LB treatment which is more likely to affect voltage fluctuations than outages, 15% of households and 14% of businesses report that they would be willing to pay more for stable voltage than any other aspect of reliability. These respondents could therefore experience the highest benefit from LB construction.

Figure 30. Reliability Improvement Customers Would be Willing to Pay the Most For



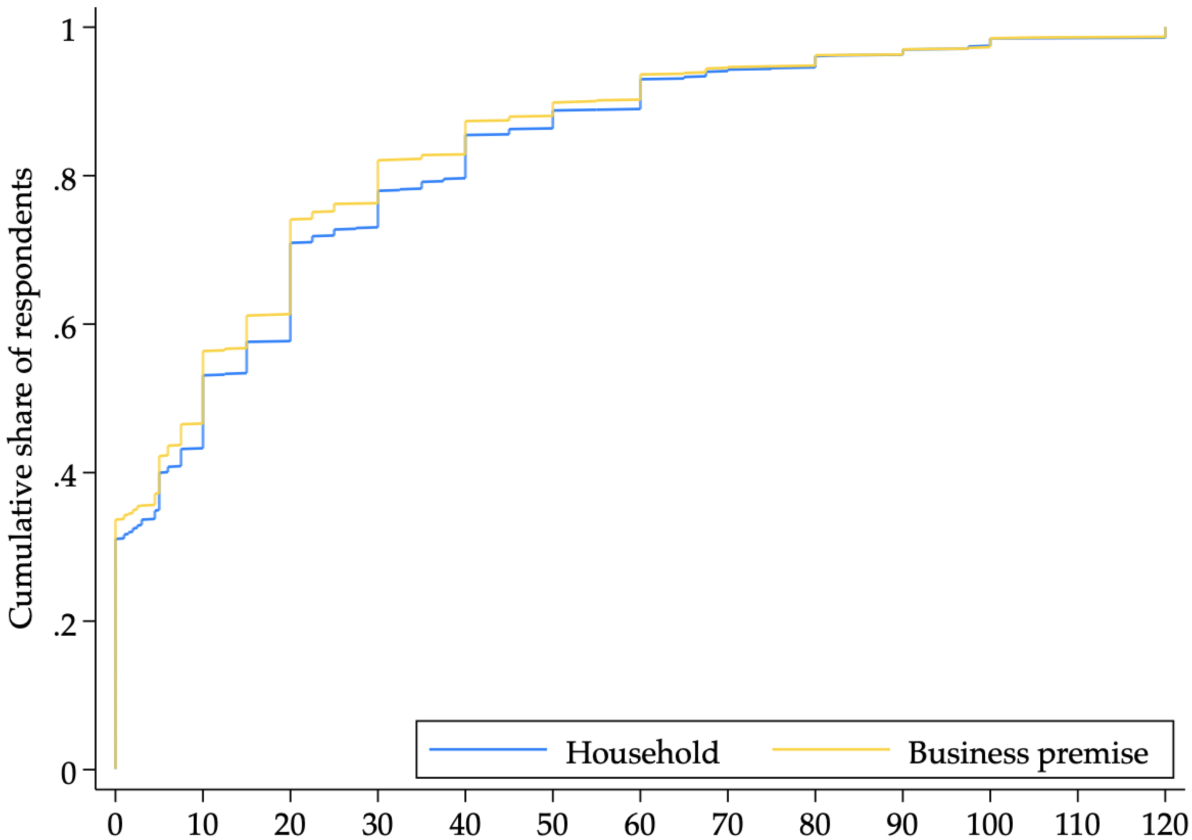
Source: Baseline survey.

Interestingly, a significant share of households (21%) and businesses (23%) report not being willing to pay for any improvements in electricity reliability. This may reflect low use of electricity among these respondents or cost constraints. We explore reasons for low WTP to improve reliability in more detail below.

After asking respondents in general what areas of reliability they would pay to improve, we then ask a series of questions to specifically elicit WTP. We begin by presenting respondents with a hypothetical scenario in which they could pay a certain amount per month (as a fixed flat fee on top of what they spend on electricity based on their consumption levels) to access a perfectly reliable electricity connection – stable voltage and no outages. We then present them a series of choices between paying a certain amount to access this perfectly reliable electricity or keeping their current electricity connection and reliability issues. For all respondents, we start with a randomly selected amount (either 20, 40, 60, or 80 GHS), and then sequentially either increase or decrease the offered price based on whether they accept or reject the connection. This allows us to isolate WTP within a certain range.

Figure 31 shows the distribution of monthly WTP for perfectly reliable electricity for both businesses and households. The distribution for businesses is to the left of that for households, indicating that businesses are in general willing to pay less for perfect reliability. Around one-third of both households (31%) and businesses (34%) are not willing to pay anything for perfectly reliable electricity. The median respondent is willing to pay GHS 10 (USD 1.5) per month for perfectly reliable electricity, which corresponds to 15% of monthly electricity spending for households and 12% for businesses. But many respondents indicate being willing to pay a large amount per month for reliable electricity. Over 11% of households and 10% of businesses are willing to pay GHS 50 (USD 7.6) or more per month, and around 7% of each indicates being willing to pay more per month to access a perfectly reliable connection than they report having paid per month for their electricity consumption over the past 3 months. These results indicate that a subset of households and businesses would benefit most from reliability improvements in LB treatment sites.

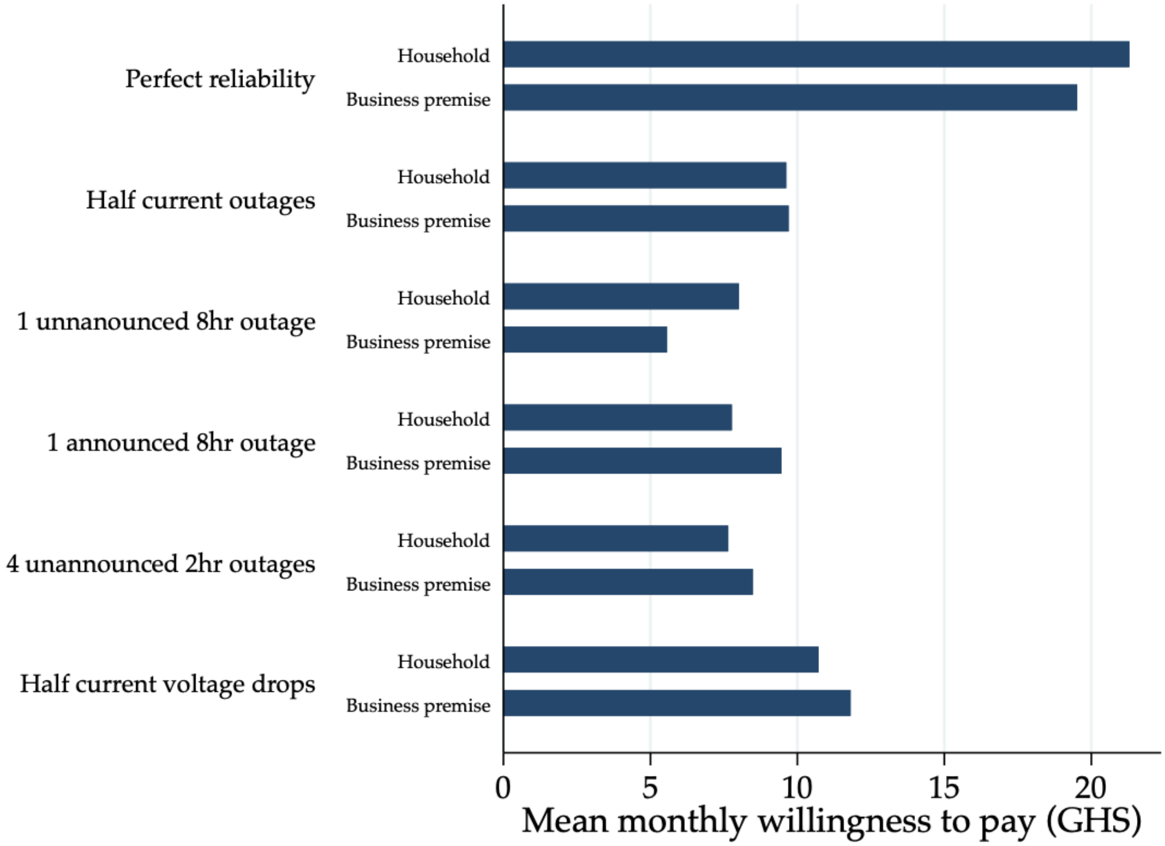
Figure 31. Distribution of Monthly Willingness to Pay for Perfectly Reliable Electricity



Source: Baseline survey.
Note: Values capped at the value for the 99th percentile.

Following the elicitation of WTP per month for a perfectly reliable electricity connection, we next asked respondents for their WTP for alternative scenarios with different types of reliability issues, using their WTP for perfect reliability as a reference point. Figure 32 summarizes mean WTP for households and businesses across these scenarios. Households report being willing to pay GHS 21.3 (USD 3.2) per month on average to access perfectly reliable electricity, compared to GHS 19.5 (USD 3.0) for businesses.

Figure 32. Willingness to Pay for Particular Reliability Improvement Scenarios



Source: Baseline survey.
Note: All subsequent WTP elicitation prompts respondents for how much they would be willing to pay for an electricity connection that is perfectly reliable except for a given issue, e.g., having one unannounced 8-hour outage each month (but not other reliability issues).

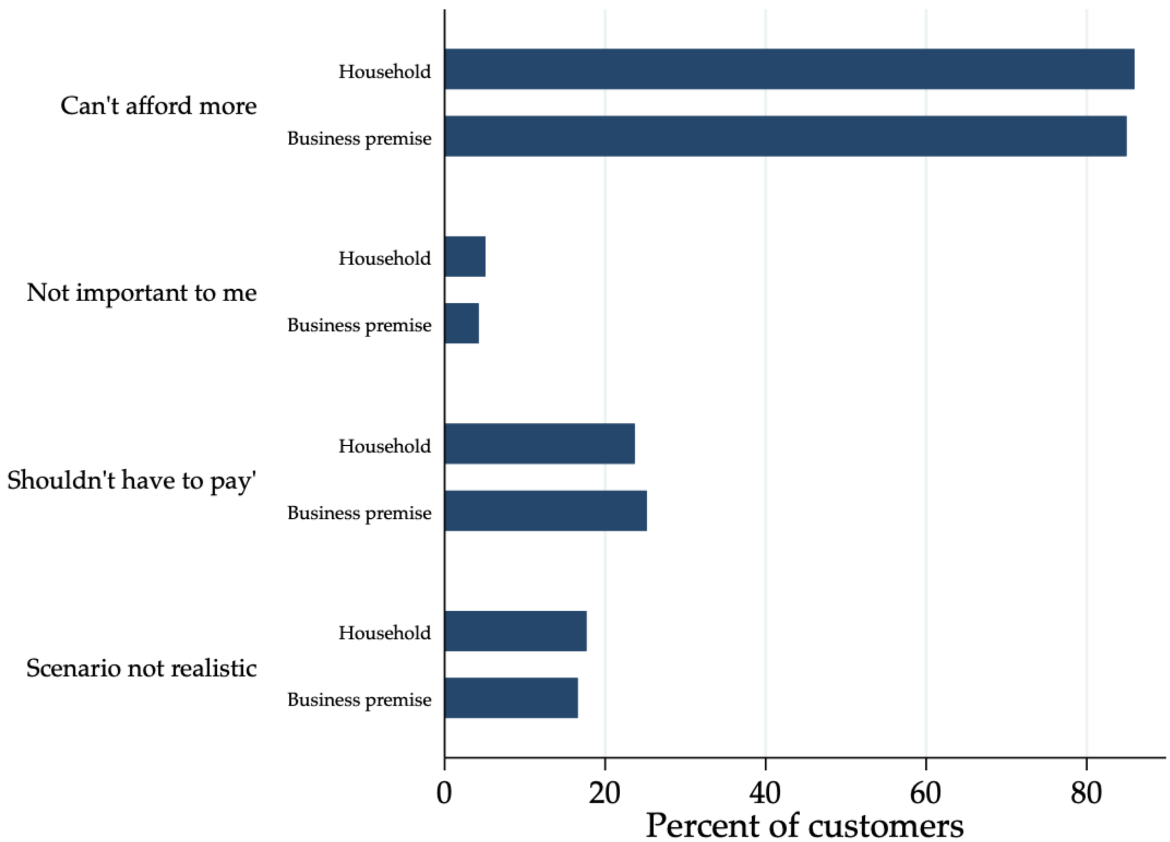
The difference in WTP between the scenario with perfect reliability and the scenarios where the electricity is perfect except for the specific given issue allows us to estimate the cost of those specific issues to customers. Mean WTP is fairly similar for both households and businesses for all other scenarios at between GHS 5-10. Of all the given scenarios, mean WTP is slightly higher (GHS 11) for a scenario with perfect reliability except for having half as many voltage drops per month as the respondents currently experience. This suggests that respondents view this scenario as closer to "perfect" reliability, and thus that voltage drops are less costly to customers.

Households view scenarios with 1 unannounced 8-hour outage per month, 1 announced 8-hour outage per month, and 4 unannounced 2-hour outages per month as equivalent, being willing to pay around GHS 8 per month for all of these. This indicates that households care less about the nature of the outages than about the total duration of outages. Businesses, however, have more distinct valuations. Businesses view 1 unannounced 8-hour outage as the most costly (based on being willing to pay less for this scenario), and 1 announced 8 hours outage as the least costly, with 4 unannounced 2-hour outages in between. This is likely a function of how such outages would affect business activities. An unannounced 8-hour outage would mean stopping any electricity-related activity for a full work day with no ability to plan for it. An announced outage could be planned for, while shorter outages would be less disruptive.

Both households and businesses are willing to pay more for a scenario with half of their current monthly outages than for scenarios with 8 hours of outages, suggesting that half of their current outage hours is less of a burden than 8 hours. This is unexpected, as the median respondent reports 24 hours of outages in the past 30 days. Respondents may prefer to have a diminished version of the reliability issues they currently face than a fixed number of outages and outage hours.

For respondents that reported not being willing to pay the initial amount proposed for the perfectly reliable electricity connection, we asked them to give the reasons for not being willing to pay more. As shown in Figure 33, the reasons are similar for households and businesses, with not being able to afford more the most common (85% of respondents). Less than 5% of respondents indicate that it is because electricity reliability is not important. Seventeen percent indicate that the proposed scenario is not realistic – they may not trust that they would actually receive reliable electricity after paying for it. Finally, 25% of respondents state that they should not have to pay anything additional for reliable electricity: they pay for electricity and the utility should make sure it is reliable.

Figure 33. Reasons for Not Being Willing to Pay More for Perfectly Reliable Electricity



Source: Baseline survey.

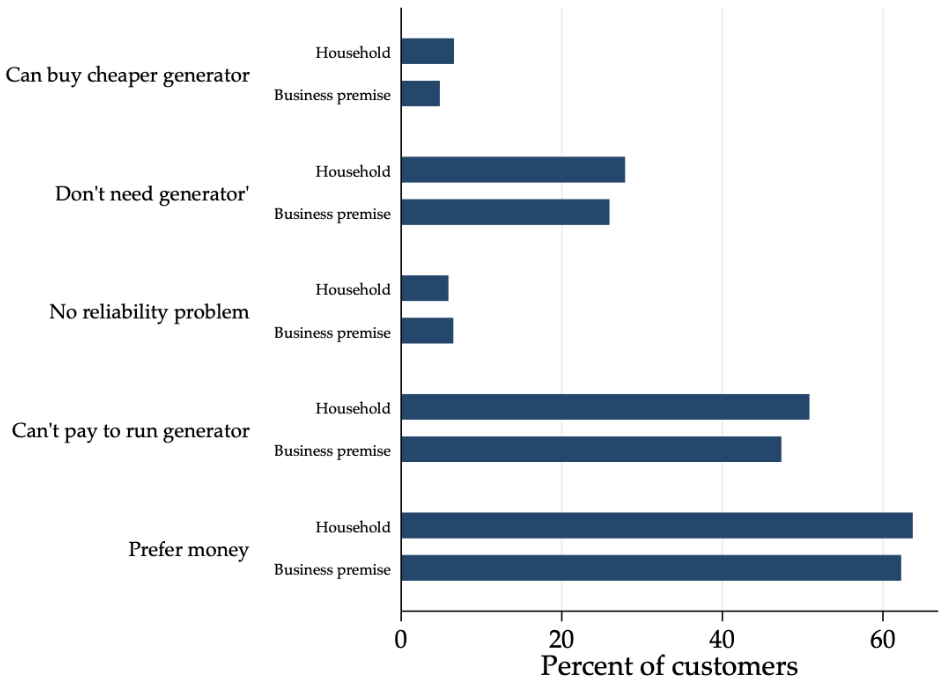
In addition to asking respondents for their WTP for reliable electricity, we also asked all respondents that did not have generators (96% of respondents) how much they would be willing to pay for a generator, giving the following hypothetical scenario:

> *"Suppose you were offered a new small portable generator of size 3.5 KW with a 15-liter petrol tank. This generator would be provided to your business/household for free, but your business/household would be responsible for the costs of using the generator after receiving it (paying for fuel and for any maintenance). For example, this generator could run a refrigerator and lights for about 12 hours on a full tank, or two large freezers for about 8 hours on a full tank."*

We then offered respondents which they would prefer between receiving GHS 800 (based on an analysis of prices for simple generators available in Accra) in cash or this generator. Similar to the elicitation for WTP for perfectly reliable electricity, we then iterated through a sequence of choices, either increasing or decreasing the amount of cash offered instead of the generator based on whether the respondent chose the generator or the cash in the previous question. Respondents were told that they could use the cash for any purpose, including buying a different generator. The highest amount of cash a respondent declined in order to choose the generator is taken as the respondent's WTP for this generator.

For households, mean WTP for a generator is GHS 1967 (USD 300), and the median is GHS 900 (USD 137), with 10% not being willing to pay anything for a generator (i.e., choosing even the smallest cash amount offered over a generator). For businesses, mean WTP for a generator is GHS 2257 (USD 345), and the median is GHS 1300 (USD 198), and again 10% are not willing to pay anything. Higher generator WTP for businesses likely reflects the greater importance of being able to access electricity at a given time for businesses relative to households.

Figure 34. Reasons for Preferring Cash to a Generator



Source: Baseline survey.

Given these relatively high levels of WTP, it is somewhat surprising that more households and businesses do not own a generator, since they should be able to purchase one for less than they indicate being willing to pay. It may be the case that the elicitation approach, being hypothetical, results in estimates of WTP that are greater than what respondents would actually be willing to pay. The framing of the scenario also involves choosing between *gifts* of cash or a generator, rather than eliciting how much of their *own money* respondents would be willing to spend on a generator.

Figure 34 summarizes all the reasons given by respondents that preferred to receive GHS 800 to a similarly-valued generator (39%). The reasons are very similar for both businesses and households. Sixty-three percent state that they would simply prefer to be able to spend the money than to have a generator. Just over a quarter report not needing a generator, and similarly 6% state that reliability is not a big problem for them. Six percent also indicate that they would take the money and buy a cheaper generator. Importantly, 49% say that they could not afford to run a generator even if they had one, suggesting that ongoing as well as fixed costs are constraints to generator acquisition in this sample.

Table 11 analyzes the correlates of the amount respondents are willing to pay for two of the above scenarios (a monthly payment for a connection with perfect electricity reliability, and a one-time payment for a generator and tests whether the correlations change after including a set of additional respondent and location controls. Results are very similar with and without controls, so the discussion focuses on the estimates that include controls.

Contrary to expectations, experiencing more hours of outages in the last 30 days is negatively associated with WTP for perfectly reliable electricity, with each hour of outages decreasing WTP by GHS 0.05. Generator ownership increases WTP, likely because households and businesses that have invested in generators are those for whom outages impose the highest costs. They would therefore be willing to pay the most for reliable electricity, and have already demonstrated some WTP for reliability by investing in a generator. Households and businesses that have more types of electric appliances also have WTP: each additional appliance type increased WTP by GHS 1.49. Reliable electricity means these respondents would be better able to use and benefit from their different electric appliances.

Interestingly, respondents in LB treatment sites are willing to pay GHS 3.56 less for perfectly reliable electricity on average, despite the fact that there is no difference in their current electricity reliability (as shown in section 3.2.2). It could be the case that treatment respondents are aware of the LB construction and are anticipating some improvement in their reliability, so see less need to make monthly payments for reliable electricity connections.

WTP for a generator appears to be positively correlated with hours of outage experienced in the last 30 days. Respondents who pay someone else for electricity are willing to pay around GHS 370 less for a generator, likely reflecting the fact that they do not manage their electricity connection and do not want to pay as much for a generator that would benefit someone else. An additional electrical appliance type owned increases WTP by GHS 73. Households are willing to pay around GHS 400 less for a generator than businesses. There is no difference in generator WTP by treatment status.

To the extent that LB construction improves electricity reliability, WTP for reliable electricity should fall in treatment sites relative to control sites. We thus hypothesize a larger negative coefficient on LB treatment for perfect reliability WTP in Table 11. Similarly, we would also expect WTP for a generator to fall. Lower WTP in treatment sites relative to control sites at the end of the exposure period would indicate that reliability issues impose less costs in treatment sites, leading to lower WTP to eliminate those costs.

Table 11. Correlates of Willingness to Pay for Perfect Reliability or a Generator

	Perfect Reliability WTP (GHS)	*Perfect Reliability WTP (GHS)*	*Generator WTP (GHS)*	*Generator WTP (GHS)*
Total outage duration in past 30 days (hrs)	-0.049***	-0.047***	2.827*	2.819
	(0.014)	(0.015)	(1.628)	(1.760)
Average low voltage hours per day in past 30 days	-0.115	-0.085	-22.039	-17.921
	(0.204)	(0.205)	(17.573)	(17.160)
Has generator	13.286**	11.698**	-	-
	(5.885)	(5.590)		
Pays someone else for electricity	2.338	1.961	-373.741**	-368.389**
	(3.303)	(3.070)	(165.781)	(168.538)
Total count of appliance types owned	1.897***	1.493***	109.581***	73.517**
	(0.393)	(0.458)	(30.814)	(35.752)
LB Treatment	-3.835**	-3.560**	174.711	173.159
	(1.639)	(1.610)	(134.411)	(135.433)
Respondent is a household only	-1.053	-0.787	-445.504***	-392.579***
	(1.447)	(1.523)	(116.656)	(123.832)
Outcome Mean	20.51	20.53	2095.71	2095.48
Observations	1989	1985	1817	1813
Additional Controls	No	Yes	No	Yes

Source: Baseline survey.
Notes: Columns indicate the outcome variable in the regressions. Outcome values are trimmed at the 99th percentile. Rows report estimated coefficients for particular variables from regressions of the outcome on a set of variables. Standard errors clustered at the site level are included in parentheses. Asterisks indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Additional controls included in particular specifications but not displayed in the output for simplicity include respondent age, sex, and level of education, dummies for whether the tenants own or rent the premises, a dummy for whether the tenants pay a landlord for electricity or manage their meter directly, the count of mobile phones owned at the premises, and the latitude and longitude for the survey site centroid.

3.5 Evaluation Question 4

How long does it take households and businesses to make lumpy investments in power-consuming technology when the reliability of the grid improves?

Households and businesses do not use electricity directly but rather through a variety of electric appliances—power-consuming technology. Customers whose electricity is not reliable should be less willing to invest in electric appliances because they cannot guarantee they will be able to use and benefit from them. When there is a risk of voltage fluctuations, customers also face the risk that their appliances could be damaged.

As electricity reliability improves, households and businesses may choose to invest more in power-consuming technology as their ability to benefit from such investments increases, if they believe that the reliability improvements are large and likely to last. It is unlikely that such changes will be detectable by the end of the exposure period for the line bifurcation construction treatment, as improvements in reliability may not be very large (particularly as there is still risk from outages due to factors beyond the local LV network), as perceptions of reliability will take time to change, and as customers may not believe improvements in reliability are permanent even if they do perceive some improvement.

Consequently, we do not include investment in electric appliances in the program logic for this evaluation.

Nevertheless, under this evaluation question we explore baseline appliance ownership and characteristics, as well as appliance purchase plans. This allows us to better understand how electricity is used, and therefore how customers in treatment sites may benefit from LB construction. Asking about appliance purchase plans further allows us to test whether there are any changes due to treatment at the end of the exposure period, which may be too short to observe changes in appliance ownership but may be long enough to affect customers' *plans* about which appliances they might invest in. Questions about appliance purchase plans can also provide insight into consumer perceptions of reliability and awareness of any reliability improvements.

3.5.1 Appliance Ownership

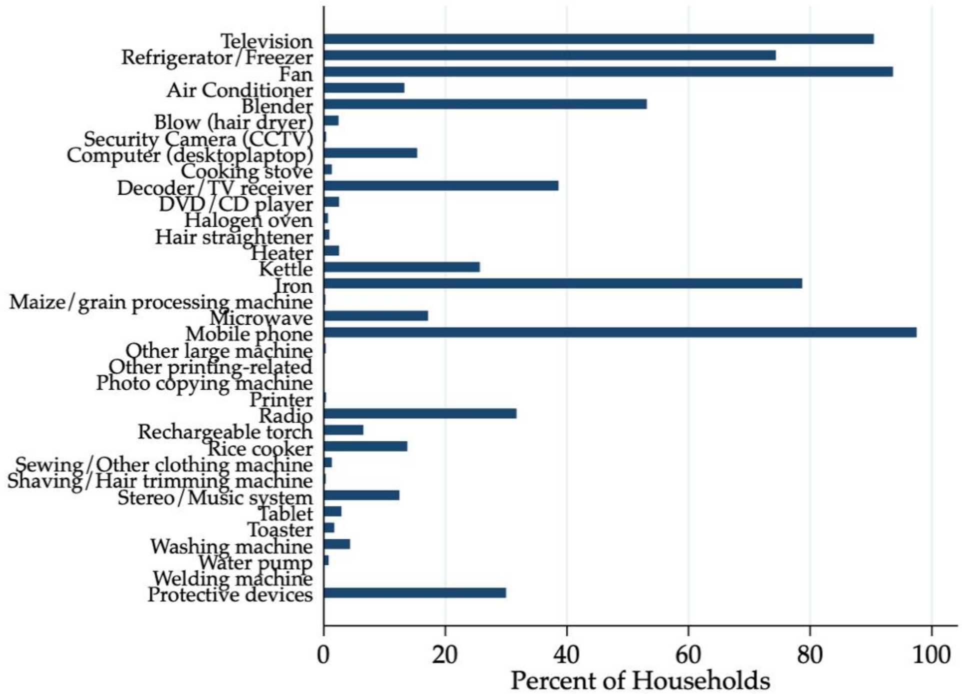
Summary:

1. *Households typically own 4 different types of appliances. The most common are mobile phones (99% of households), fans (94%), televisions (90%), electric irons (79%), and refrigerators/freezers (74%).*
2. *Businesses typically own 3 different types of appliances. The most common are again mobile phones (99% of businesses), fans (75%), televisions (52%), and refrigerators/freezers (49%), potentially reflecting the small and less formal nature of most sample businesses.*
3. *Fifteen percent of businesses have electric sewing machines or other clothing-related machines, consistent with 14% of businesses being engaged in clothing-related activities. Just 9% of businesses report having any non-electric machines for business purposes, the most common of which are manual (i.e., foot pedal-operated) sewing machines.*
4. *Most household and business appliances were acquired within the last few years, since 2018.*

Figure 35 summarizes the share of households reporting owning each type of appliance asked about in the survey. All respondents are asked specifically about ownership of televisions, refrigerators, fans, air conditioners, and mobile phones, and then asked to name all other appliances they own at their dwelling. The most common other types of appliances held are electric irons (79%), blenders (53%), TV decoders/receivers (39%), and radios (32%). The median household owns 4 different types of appliances, and nearly all own 3 or more.

Table 12 provides additional details on appliance ownership for a set of common appliances: mobile phones, fridges/freezers, televisions, fans, and air conditioners (ACs). These include four of the five most common appliances. Air conditioners are less common but represent an important large electric appliance. All but 7 households own at least one mobile phone; the median household has two. Most of these are smartphones rather than feature phones. Seventy-four percent of households have a refrigerator or freezer; very few have more than one. Ninety percent of households have a television, and a few households own more than one. Fans (94% of households) are used for cooling much more commonly than air conditioners (13%), and many households own multiple fans. In general, these appliances were acquired fairly recently, with the median owner acquiring a given appliance in 2018 or 2019, though a few households own much older appliances.

Figure 35. Household Ownership of Electric Appliances



Source: Baseline survey.

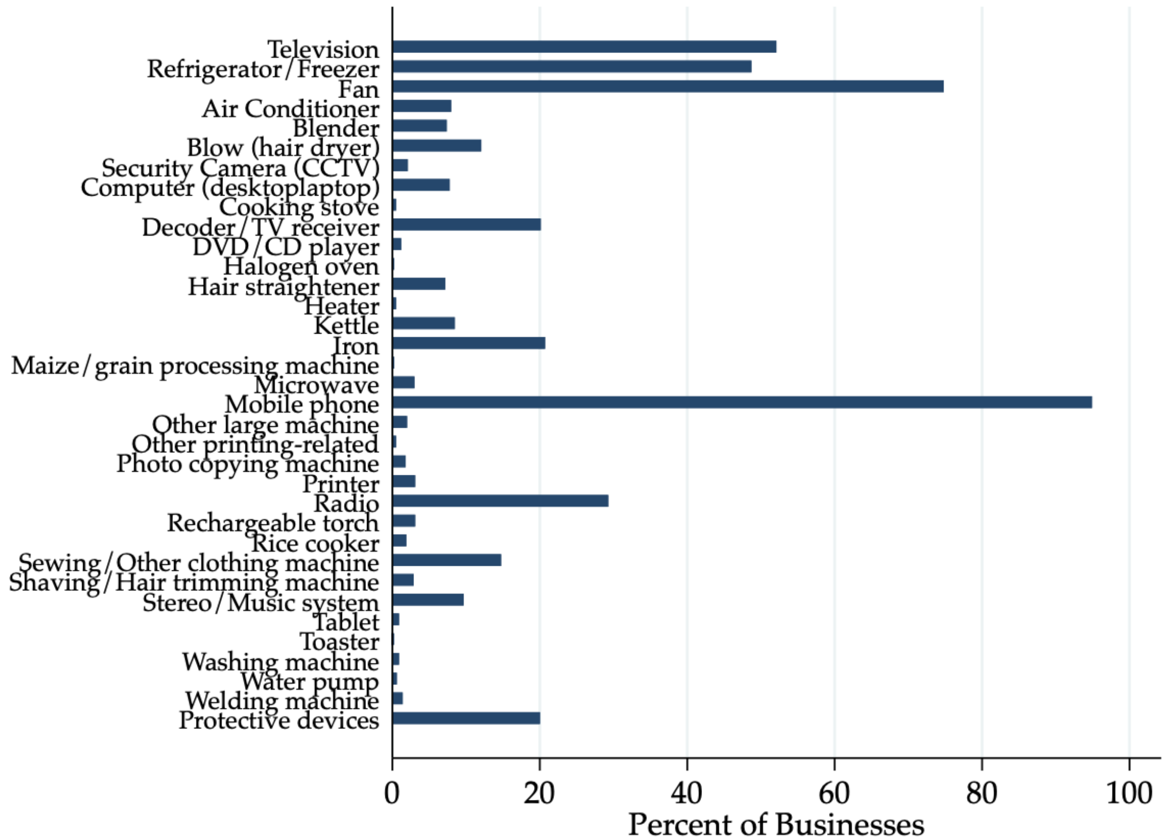
Table 12. Summary Statistics for Household Ownership of Common Appliances

	N	Mean	SD	Min	25th	50th	75th	Max
Total count of appliance types owned	998	4.80	2.85	0	3	4	6	20
Total value of TVs and fridges (GHS)	998	1,859.93	1,902.08	0	700	1,500	2,300	25,100
Mobile Phones								
Count owned	998	2.34	1.46	0	1	2	3	10
Share of smart phones	991	0.71	0.37	0	0	1	1	1
Refrigerator/Freezers								
Count owned	998	0.87	0.67	0	0	1	1	5
Year most recently acquired	680	2017	4.29	1990	2015	2018	2019	2021
Televisions								
Count owned	998	1.07	0.60	0	1	1	1	8
Year most recently acquired	845	2017	3.44	1996	2016	2018	2020	2021
Fans								
Count owned	998	1.65	1.20	0	1	1	2	11
Year most recently acquired	831	2018	3.54	1990	2016	2019	2020	2021
Air Conditioners								
Count owned	998	0.15	0.45	0	0	0	0	7
Year most recently acquired	125	2018	2.20	2009	2017	2019	2020	2021

Source: Baseline survey.

Figure 36 summarizes the share of businesses reporting owning each type of appliance asked about in the survey. The most common types of appliances held, other than phones, televisions, refrigerators, and fans, are radios (29%), irons (21%), and TV receivers (20%). Fifteen percent of businesses have electric sewing machines or other clothing-related machines, consistent with 14% of businesses being engaged in clothing-related activities.

Figure 36. Businesses Ownership of Electric Appliances



Source: Baseline survey.

The median business owns 3 types of electric appliances, with most owning at least 2 (Table 13). Just 9% of businesses report having any non-electric machines for business purposes, in line with the fact that most businesses are engaged in services.

The most common appliances owned by businesses are the same as those for households, perhaps reflecting the small and less formal nature of many businesses. All but 8 businesses own at least one mobile phone. About three quarters of mobile phones owned by businesses in the sample are smartphones rather than feature phones. Forty-nine percent of businesses have a refrigerator or freezer. This may reflect the 39% of businesses engaged in general retail or in food and beverage services. Fifty-two percent of businesses have a television, potentially due to the fact that most businesses are in the service sector so televisions may serve as entertainment for customers (and employees). Fans (75% of businesses) are again used for cooling much more commonly than air conditioners (8%). As with households, businesses typically acquired their appliances fairly recently, with the median owner acquiring a given appliance in 2019.

Table 13. Summary Statistics for Business Ownership of Common Appliances

	N	Mean	SD	Min	25th	50th	75th	Max
Total count of appliance types owned	1004	3.00	2.06	0	2	3	4	19
Total value of TVs and fridges (GHS)	1004	1104.76	1465.78	0	0	650	1675	13700
Mobile Phones								
Count owned	1004	1.97	1.76	0	1	1	2	20
Share of smart phones	996	0.74	0.38	0	0	1	1	1
Refrigerator/Freezers								
Count owned	1004	0.70	0.88	0	0	0	1	6
Year most recently acquired	450	2017	3.80	1990	2016	2019	2020	2021
Televisions								
Count owned	1004	0.58	0.68	0	0	1	1	8
Year most recently acquired	485	2018	3.80	1992	2016	2019	2020	2021
Fans								
Count owned	1004	1.10	1.27	0	0	1	1	20
Year most recently acquired	680	2018	3.32	2000	2017	2019	2020	2021
Air Conditioners								
Count owned	1004	0.13	0.67	0	0	0	0	14
Year most recently acquired	69	2019	2.81	2005	2018	2019	2020	2021
Non-electric Machines								
Count owned	1001	0.78	15.56	0	0	0	0	450
Year most recently acquired	75	2014	7.41	1990	2009	2017	2020	2021

Source: Baseline survey.

The endline survey will compare changes in appliance ownership and consider the dates when appliances were purchased. Differences by treatment status would indicate that respondents were able to observe an improvement in power and make appliance investments.

3.5.2 Appliance Purchase Plans

Summary:

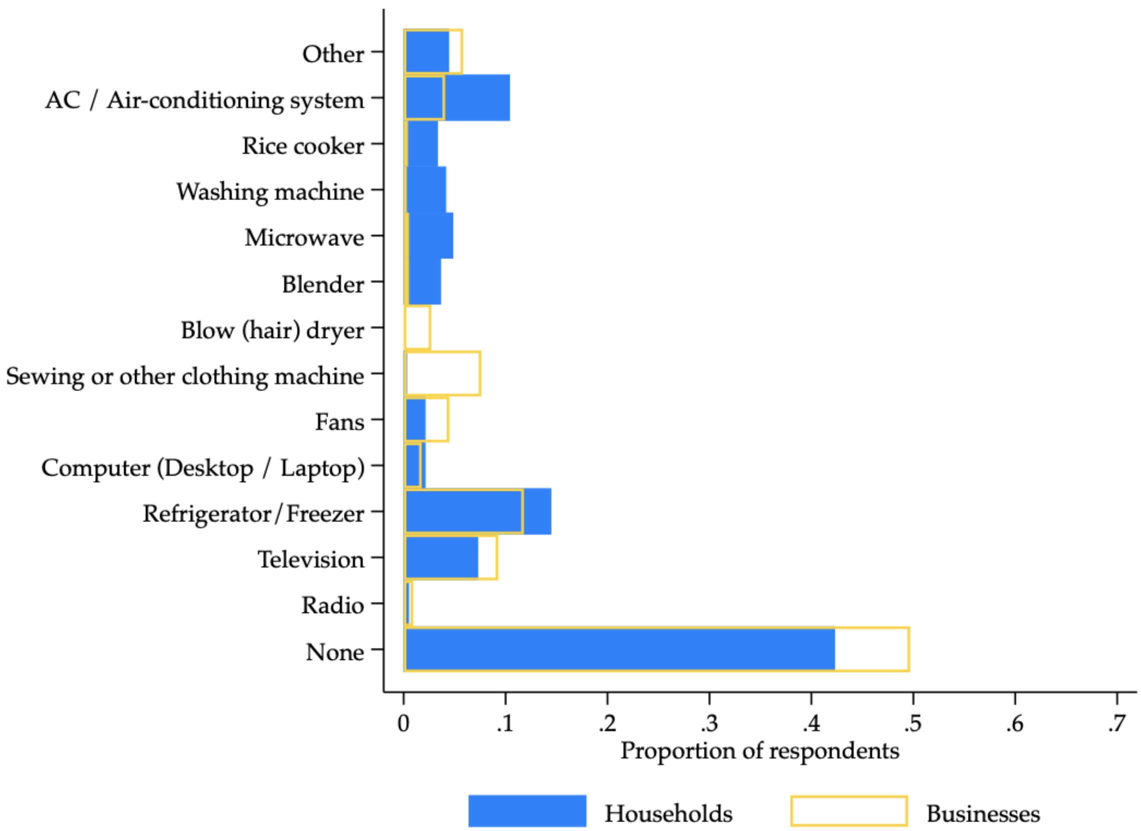
1. *Around half of respondents (40% of households and 50% of businesses) have no plans to purchase an additional appliance, either currently or in a hypothetical scenario with perfectly reliable electricity.*
2. *For households, the top 3 appliances to be purchased, with or without better reliability, are refrigerator/freezers, televisions, and air conditioning systems.*
3. *Refrigerators and televisions are the most commonly-named appliances for businesses, but around 5% would purchase a blow dryer (16% of businesses are engaged in personal care services, including hair care) and around 10% would purchase a sewing machine or some other clothing-related electric appliance (14% of businesses are engaged in clothing manufacture or repair).*

We asked all respondents two questions about appliance purchase plans. First, we ask "*What will be the next electrical appliance that you will purchase for this location?*" Then, we ask "*Imagine that you had reliable electricity 24 hours a day 7 days a week. Which other appliances would buy then, that you are currently not planning to purchase?*" The results are presented in Figures 37 and 38. Respondents appear to have taken these questions seriously, as most report that they would purchase just one or two appliances, if any, rather than reporting a list of appliances that they would *like* to own but would not realistically acquire.

A large share of respondents (around 40% of households and 50% of businesses) have no plans to purchase an additional appliance, either currently or with perfectly reliable electricity. This finding makes it unlikely that any change in electric appliance ownership will be realized by the end of the LB treatment exposure period.

For households, the top 3 appliances to be purchased, with or without perfect reliability, are refrigerator/freezers, televisions, and air conditioning systems. These include households who already own fridges and televisions, which are common. More households report that they would purchase various appliances if they had perfectly reliable electricity, though this is also partly because households could name multiple appliances for this question.

Figure 37. Next Electric Appliance Respondents Plan to Purchase

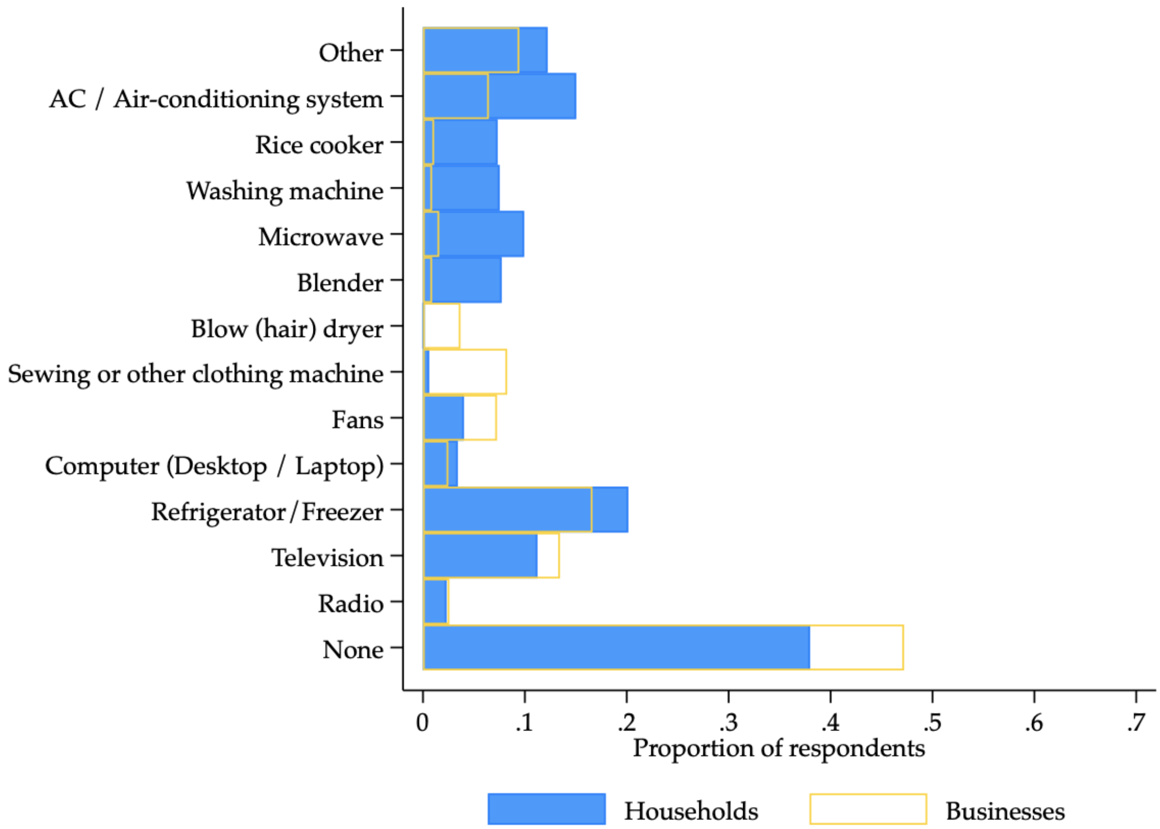


Source: Baseline survey.

Patterns in appliance purchase plans differ somewhat for businesses. They are much less likely to report planning to purchase any of the types of household convenience appliances some households mention, and more likely to plan on purchasing two specific appliances that may relate to their business activities. Around 5% of business would purchase a blow dryer (16% of businesses are engaged in personal care services, including hair care) and around 10% would purchase a sewing machine or some other clothing-related electric appliance (14% of businesses are engaged in clothing manufacture or repair).

Despite these differences, refrigerators and televisions are the most commonly-named appliances for businesses, and like households their relative shares reporting they would buy particular appliances are similar for the next appliance businesses plan to purchase as for the appliances they would purchase with perfect reliability.

Figure 38. Additional Appliances Respondents Would Purchase With Perfectly Reliable Electricity



Source: Baseline survey.

The endline activity will analyze whether changes in patterns of appliance purchase plans differ by treatment status. In particular, we hypothesize that if treatment respondents have begun to observe some improvements in reliability they might be less likely to report no plans to purchase any additional appliances.

3.6 Evaluation Question 5

> *What is the Program's overall impact on the profitability and productivity of enterprises? What are the mechanisms or channels through which these impacts occur?*

Improved electricity reliability could affect business profits in two main ways. First, more reliable electricity could lead business to reduce their use of alternative energy sources in favor of more electricity use (discussed in section 3.3.1), which would reduce business costs on the assumption that electricity is less costly than its alternatives or back-ups. Second, improved reliability could increase business revenues by reducing interruptions to business (discussed in section 3.4.2) or by increasing use of productive electric appliances.

***Summary**:*

1. *The median business in the sample has estimated revenues of USD 183 and profits of USD 61 over the past month.*
2. *LB treatment and measures of electricity reliability are not significantly correlated with revenues or profits at baseline.*
3. *Profits are higher on average for businesses engaged in retail, with more employees, and with a larger share of male employees.*

This section presents baseline descriptive statistics for business profits, revenues, and costs, and analyzes correlates of business profits and revenues. Business profits are the main socioeconomic outcome of interest in this evaluation, and the endline report will analyze whether profits have increased for businesses in LB treatment sites relative to those in control sites. As any differences in profits due to LB treatment will not be observable until the endline survey, this section will not include a discussion of mechanisms other than to point out business characteristics associated with higher profits in the cross-section of businesses. The endline report will draw on the analyses in sections 3.3.1, 3.4.2, and 3.7 to discuss what mechanisms might explain any observed impacts on profits.

Table 14 presents summary statistics for business profits, revenues, and costs over the 30 days prior to the baseline survey interview. The sample size for these questions is smaller than the number of businesses in the sample (1,004), as many respondents were not able to confidently answer these questions and instead said “I don’t know”. The summary statistics are therefore descriptive of the sample of businesses able to provide an estimate of these values; these may differ from businesses that did not provide any estimates.

Mean revenues over the 30 days prior to the interview are GHS 3,462 (USD 528), with a median of GHS 1,200 (USD 183). The mean is pulled upward by one business with reported revenues of GHS 600,000; no other business has profits above GHS 100,000. Figure 5 in section 3.1.2 shows the distribution of reported revenues after capping revenues at the value for the business at the 99^{th} percentile.

We ask business about costs in two specific categories which should be common across industries: wages and benefits paid to employees and materials/inventory. Mean wages and benefits paid in the past month are GHS 467 (USD 71), but as is expected when most businesses have only 1 employee (the owner), the median business has no wage costs (instead paying themselves out of profits). Mean materials costs are GHS 1659 (USD 253) with a median of GHS 500 (USD 76). Total reported business costs consist of wages, benefits, and materials along with spending on electricity and energy sources over the last 30 days (these are likely not comprehensive as businesses may have a variety of other expenses). Mean spending is GHS 2,293 (USD 350) with a median of GHS 990 (USD 151). As with estimated revenues, the means for estimated costs are pulled upward by one business with much higher costs than any others; their total reported spending is GHS 204,000 while the next-highest is GHS 81,000.

Table 14. Summary Statistics for Business Profits, Revenues, and Costs in the Last 30 Days

	N	Mean	SD	Min	25th	50th	75th	Max
Total revenue (GHS)	870	3,462.00	21,183.76	0	600	1,200	3,000	600,000
Total wages and benefits paid (GHS)	886	467.14	2,098.17	0	0	0	350	50,000
Total materials costs (GHS)	855	1,659.01	6,312.76	0	200	500	1,600	150,000
Total reported business costs (GHS)	817	2,293.02	8,227.49	10	435	990	2,100	204,000
Total profit (GHS)	777	716.75	1,597.69	-3,600	160	400	800	30,000

Source: Baseline survey.

The survey measures profits directly by asking "*What was the total profit the business earned during the past one month after paying all expenses including wages of employees, but not including any income paid to the business owner*" following best practice (de Mel, McKenzie, & Woodruff 2008). In general, directly reported and indirectly calculated (by subtracting costs from revenues) profits are fairly similar, but the analysis focuses on reported profits. Mean profits for the last month in the sample are GHS 717 (USD 109), with a median of GHS 400 (USD 61). As discussed in section 3.1.2, sample businesses are nearly all very small enterprises with just one or two employees engaged primarily in retail and other service activities, so do not generate very large profits. Sixty-one businesses (7.9% of those reporting profits) report zero or negative profits. Comparing reported profits to reported revenues, businesses on average generate 33% of their revenues as profits, and the median business also reports that profits are 33% of revenues.

Table 15 presents correlates of business profits and revenues at baseline. For each outcome, the first regression analyzes the correlation with just two measures of electricity reliability—total outage hours and average low voltage hours per day in the past 30 days—since these are the business conditions that LB treatment is intended to affect. The second regression includes these variables and a set of business characteristics that might be of interest for exploring mechanisms for any effects of LB treatment. The third regression includes all of the above variables along with additional respondent and location controls, for robustness. The discussion focuses on this third regression for both outcomes, though results are broadly similar across specifications. All coefficients in Table 15 can be interpreted as the amount by which profits/revenues would change (in GHS) for a one unit change in the particular variable of interest, holding all other variables constant.

Table 15 shows no significant relationship between measures of electricity reliability and either profits or revenues, despite businesses reporting that reliability is an important obstacle to business. The lack of significance on these variables may be because all businesses in the sample have similar levels of power reliability at baseline. If LB construction improves reliability in treatment sites by the end of the exposure period, businesses in these sites might have higher profits or revenues than those in control sites.

Businesses engaged in retail activities (32% of the sample) report significantly higher revenues and profits than businesses engaged in other activities. Businesses with more employees and with a greater share of male employees also report much higher revenues and profits. An additional employee is associated with GHS 94 (USD 14) more in profits per month, and having all male employees is associated with GHS 580 (USD 88) more profits than having all female employees, holding all else constant. These results highlight differences in the types of business activities that women and men engage in, and the low profits for individuals engaged in small owner-operated enterprises.

Table 15. Correlates of Business Profits and Revenues

	Monthly Profit (GHS)	Monthly Profit (GHS)	Monthly Profit (GHS)	Monthly Revenue (GHS)	Monthly Revenue (GHS)	Monthly Revenue (GHS)
Total outage duration in past 30 days (hrs)	-0.632	-0.054	0.078	-0.180	2.946	5.128
	(0.677)	(0.678)	(0.685)	(3.649)	(3.264)	(3.321)
Average low voltage hours per day in past 30 days	6.277	4.858	8.820	-26.761	-32.893	-12.078
	(9.724)	(8.730)	(8.669)	(35.944)	(35.980)	(36.217)
Business engaged in retail activities		126.318	139.780*		909.233***	855.468***
		(77.667)	(81.558)		(266.287)	(301.073)
Total employees		92.789***	93.725***		718.282***	578.147***
		(30.313)	(34.151)		(96.152)	(152.431)
Share of male employees		427.248***	580.282**		1476.074***	1546.229
		(83.526)	(243.936)		(382.804)	(1097.317)
Number of working hours per day		-20.057	-19.796		-62.710	-52.331
		(15.270)	(15.510)		(50.156)	(48.002)
Has generator		220.538	268.433		817.943	722.062
		(190.060)	(189.342)		(661.992)	(626.774)
Total count of appliance		-8.127	-7.381		-25.053	-36.245
types owned		(19.960)	(19.091)		(74.211)	(79.265)
Count of non-electric business machines		-46.735	-43.625		-784.063***	-849.872***
		(52.555)	(45.638)		(233.083)	(253.019)
LB Treatment		-39.039	-41.886		85.178	53.008
		(71.971)	(71.161)		(292.215)	(300.702)
Outcome Mean	650.15	650.74	650.61	2574.27	2579.81	2583.15
Observations	774	769	767	865	860	858
Additional Controls	No	No	Yes	No	No	Yes

Source: Baseline survey.
Notes: Columns indicate the outcome variable in the regressions. Outcome values are trimmed at the 99th percentile. Rows report estimated coefficients for particular variables from regressions of the outcome on a set of variables. Standard errors clustered at the site level are included in parentheses. Asterisks indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Additional controls included in particular specifications but not displayed in the output for simplicity include respondent age, sex, and level of education, dummies for whether the tenants own or rent the premises, a dummy for whether the tenants pay a landlord for electricity or manage their meter directly, the count of mobile phones owned at the premises, and the latitude and longitude for the survey site centroid.

Generator ownership is associated with higher revenues and profits, though this is not significant, likely because of the small number of businesses with a generator. This aligns with expectations, as investing in a generator would only be worthwhile for more profitable businesses. The count of electric appliance types owned is not associated with profits or revenues, suggesting that having a variety of electric equipment is not related to profits. Indeed, many businesses likely only need one or two types of electric appliances that directly related to their business activities. On the other hand, businesses with more non-electric productive machines have significantly lower revenues, perhaps suggesting that such machines are less productive than their electric counterparts.

Finally, being in an LB treatment site is not significantly associated with either revenues or profits at baseline. This is consistent with the finding that treatment and control sites are well-balanced on observables at this time. The endline analysis will test for a difference in revenues and profits between businesses at treatment and control sites, controlling for baseline values. Similar regressions looking at changes in business characteristics and activities will help determine potential mechanisms.

3.7 Evaluation Question 6

To what extent do small and medium firms (up to 30 employees) respond to more reliable, accessible, and/or higher quality power by: Expanding or intensifying production; Expanding employment; Investing in expanded plant or other fixed assets and/or different production technologies reliant on electricity?

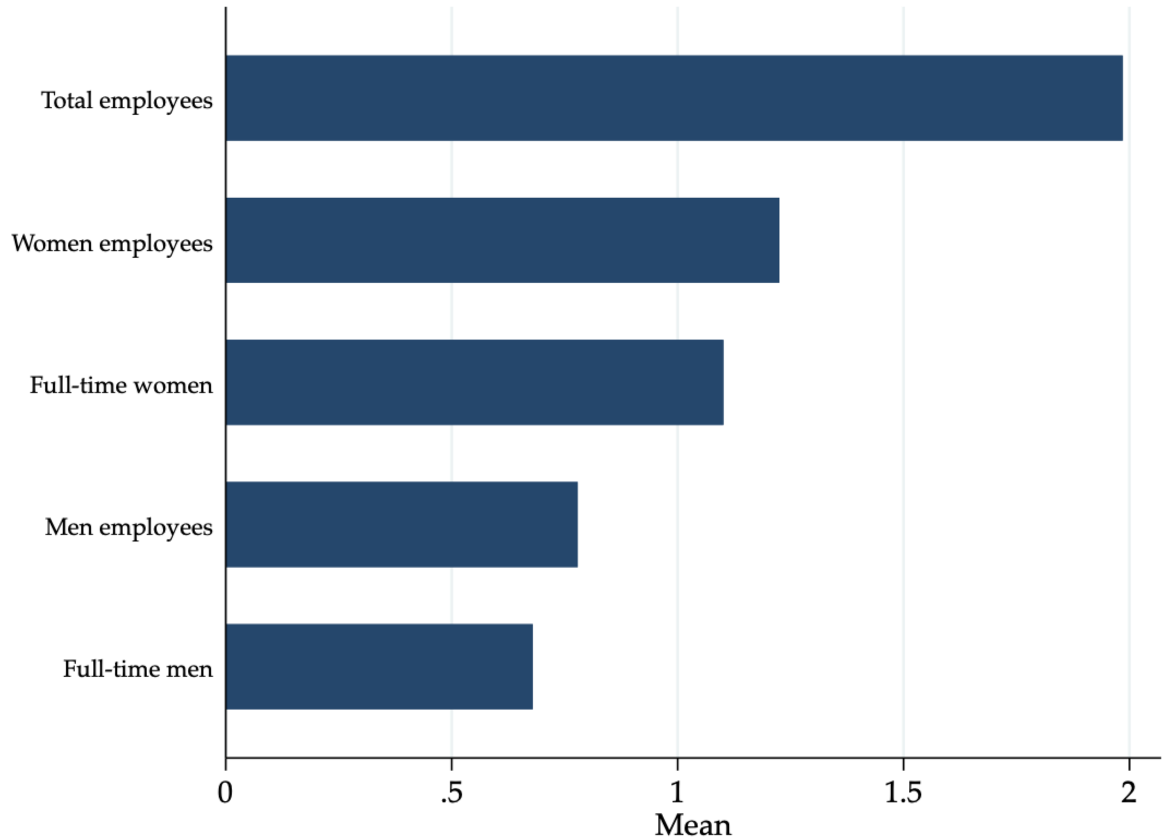
***Summary**:*
1. *Businesses in our sample have just under 2 employees on average, though the majority have just one.*
2. *A majority of businesses employ only women, and most workers across businesses are engaged full-time.*
3. *Businesses are typically open for 12 hours per day, from 8am to 8pm.*
4. *Businesses own between 6 and 7 electric appliances from three different appliance types, on average. In addition to a mobile phone and often a television and/or refrigerator, businesses own several appliances of a particular type associated with their business activity.*
5. *Around 15% of businesses own electric sewing machines, and nearly two-thirds of these own two or more. These businesses operate their sewing machines for 11 hours per day, and are more likely to have non-electric sewing machines as backups. They could therefore benefit more from reliable electricity than other businesses.*

Businesses that perceive that electricity is more reliable could respond in a variety of ways. Assuming reliability improves productivity, this could motivate increases in employment. Nevertheless, most businesses are owner-operated with just 1 or 2 employees so may be unlikely to change use of labor. Hours of operations may shift if businesses are better able to work at night, for example, or if they can complete the same work in fewer hours. Businesses might invest in more electric appliances as they could use these more reliably, and substitute away from presumably less efficient non-electric alternatives.

The endline analysis will test whether LB treatment causes changes in these business characteristics at the end of the exposure period. This baseline report reports descriptive results on business employment, working hours, and appliance ownership.

Figure 39 summarizes business employment characteristics for the sample. Businesses are quite small, with just under 2 employees on average, typically the owner and one other worker. Fifty-three percent of businesses have just one worker, and just 13 businesses (1.3%) have ten or more. A majority of employees are women, and nearly all employees are occupied full-time. Most businesses are either all-female or all-male, even among businesses with more than one employee. Forty-three percent of businesses with two or employees have all female employees, and 22% have all male employees.

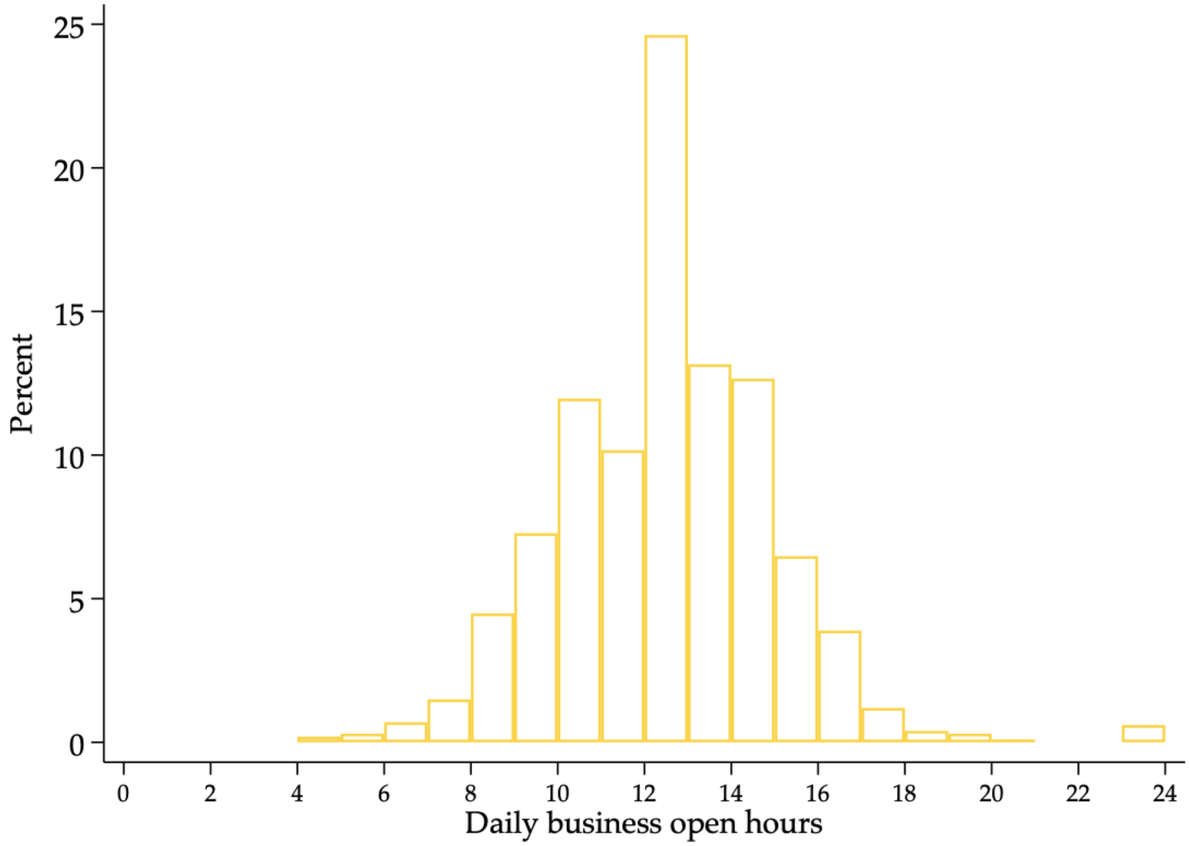
Figure 39. Number of Employees at Surveyed Businesses



Source: Baseline survey.

Figure 40 shows the distribution of the number of hours that businesses are typically open each day. The mean and median are both 12 hours; businesses most commonly open at 8am and close at 8pm. Fifty percent of businesses are open between 10 and 14 hours each day. Nearly all businesses open no later than 9am. Just over three-quarters of businesses are open during non-daylight hours (as proxied by being open either before 6am or after 6pm), mostly at night, as 71% of businesses close after 6pm. The potential effect of improved electricity reliability on business hours is ambiguous. Businesses might work longer hours if these hours are more productive and profits increase, or they might work fewer hours if they can reach target output or revenue levels in a shorter amount of time. Businesses might also be more likely to stay open at night with more reliable electric lighting.

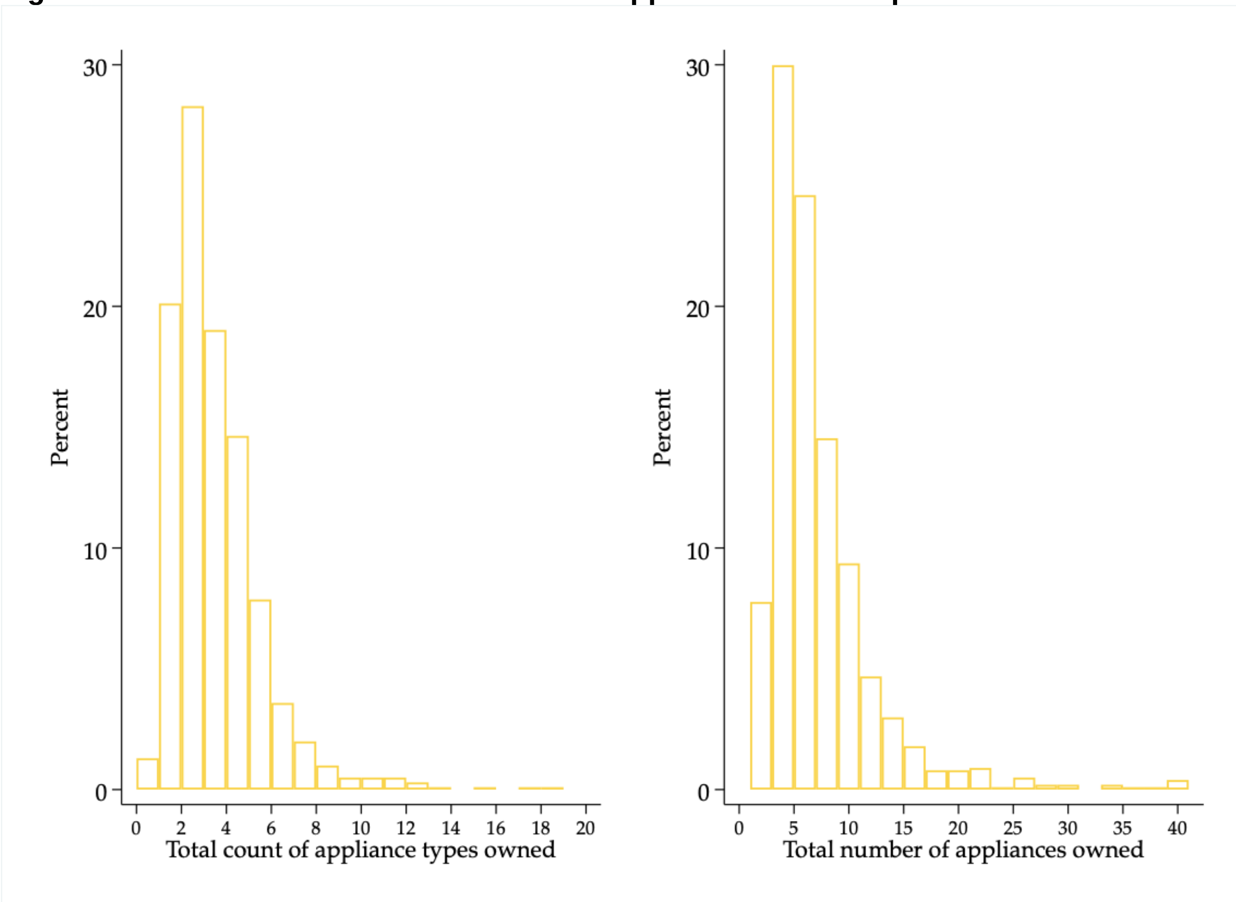
Figure 40. Business Working Hours



Source: Baseline survey.

The left panel of Figure 41 shows the distribution of the number different types of electric appliances businesses own. The mean and median are both 3 types of appliances, and 83% of businesses have 4 or fewer types of appliances. We report on what types of appliances businesses have in section 3.5.1. As noted in section 3.6, having many different appliance types may not have any correlation with business revenues or profits, as most business activities are specialized and only need a small number of types of productive equipment, such as a refrigerator for a retail shop and an electric sewing machine for a tailoring shop. Consequently, the number of electric appliances owned across types might better reflect the scale of business activities than the number of different appliance types. The right panel of Figure 41 reports the distribution for this variable.

Figure 41. Distribution of Business Electric Appliance Ownership

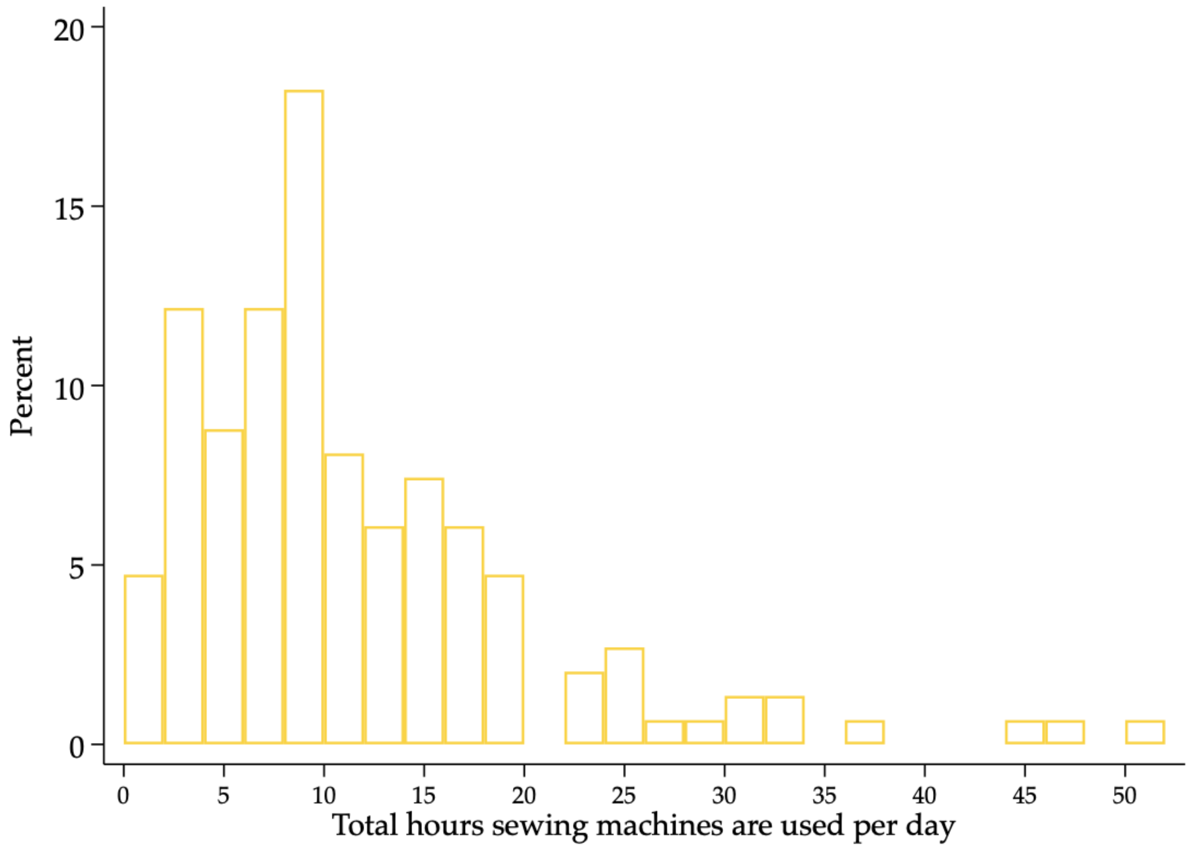


Source: Baseline survey.

The mean number of electric appliances owned is 6.8, and the median is 5. Eighty-six percent of businesses have 10 or fewer electric appliances. Businesses with three or fewer appliances typically have one of each type of appliance; those with five or more appliances report have several of a particular type of appliance, usually associated with their business activity.

For example, many businesses own multiple electric sewing machines. Fourteen percent of businesses are primarily engaged in manufacture or repair of clothing products, and 14.7% of businesses report owning an electric sewing machine. Of these 148 businesses, 93 (63%) own two or more sewing machines. For each sewing machine, we ask businesses to report the average number of hours per day that it is used. Figure 42 shows the distribution of hours of use for sewing machines among business that own one. The mean is 11.1 hours and the median is 8.6, suggesting that businesses with these electric appliances are spending a fairly large share of their working hours using these machines. Such businesses could thus be among those that would most benefit from more reliable electricity, and the endline survey will specifically analyze impacts on these businesses.

Figure 42. Distribution of Daily Hours of Sewing Machine Use Among Business with Sewing Machines (148)



Source: Baseline survey.
Note: Hours are the total across individual machines. For example, if three machines are each used for 8 hours per day, the total hours is 24.

In addition to electric appliances, businesses may own non-electric productive machines. Just 77 of the businesses (7.7%) report having at least one such machine. The most common are manual (i.e., foot pedal-operated) sewing machines. Twenty-five of the 37 businesses with more than one non-electric machine are engaged in manufacture or repair of clothing, further highlighting how this sector might particularly benefit from more reliable electricity.

3.8 Evaluation Question 7

> *Are customers notified ahead of schedule of their outages? What is the differential impact on customers between known and unknown outages? What is the impact of known versus unknown outages on customer relations?*

In the original proposal for this evaluation, we had planned to encourage baseline survey respondents to download the PowerWatch mobile app. This app, which was under development at the time of the proposal, was intended to provide real-time information on electricity outages based on GridWatch devices to customers. The idea was that providing additional information about outages to customers would affect their perspectives about the reliability of electricity and the performance of the electricity utility, and the original evaluation question sought to analyze this. The team experienced difficulties with the development of this app, however, and it was not included in the baseline survey. The current evaluation question 7 is similar in seeking to explore how information about outages affects customers, but considers a different type of information: prior notifications about planned outages.

Many types of outages in Accra are planned in advance, including load shedding and maintenance operations. Although load shedding operations have been greatly reduced in Ghana since the end of the Dumsor crisis in 2016, they still account for nearly 20% of outages reported in 2019 ECG situational reports, while planned outages account for 28%. Thus, just under half of feeder-level outages in 2019 were planned in advance, though the share of total outages planned in advance will be lower, as many outages occur below the feeder level. In cases where outages are planned, ECG typically disseminates information on the timing and location of outages through various media, including radio and social media. Customers that are following ECG outage announcements may therefore be forewarned for a share of the outages they experience, which may allow them to plan around the outages. Respondents report what share of outages in the last month they were aware of ahead of time. Responses capture both the share of outages that are announced in advance and the level of respondent attentiveness to these announcements.

As planned outages are not expected to vary as a result of LB construction, we do not expect any difference in awareness of or attentiveness to planned outages by treatment status. This question is therefore separate from the evaluation of the LB construction activities, but this may still be of interest to the same stakeholders. As discussed in section 3.4, unpredictability of outages is reported by businesses as the main obstacle they face with unreliable electricity, and businesses are willing to pay around one and a half times as much for a connection with a given level of electricity outages if those outages are announced in advance. This question therefore touches a key component of the issues with electricity reliability, even if it is not a component that the LB treatment addresses.

We first present descriptive statistics on the share of outages that respondents report being aware of in advance, the amount of advance notification they receive, and their sources of information, and analyze correlates of being more aware of outages in advance. We then present respondent perspectives on the performance of the electricity network, using responses to a question about whether Dumsor is back as a proxy for perspectives on electricity quality, and analyze correlates of these perceptions.

3.8.1 Outage Awareness

Summary:

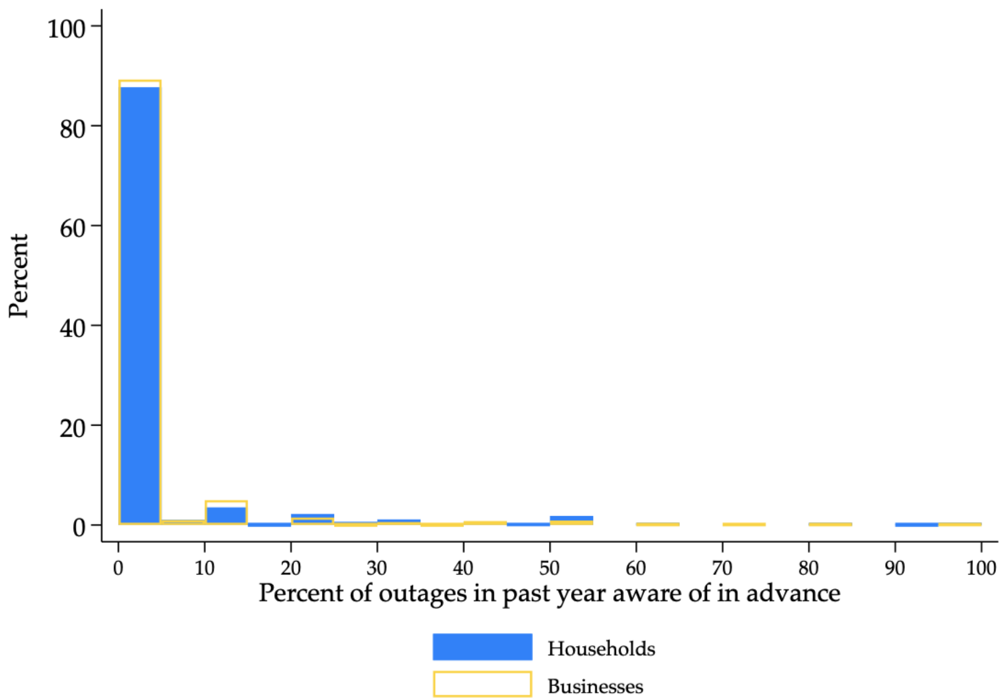
1. *Most customers (87%) report not being aware of any outages ahead of time in the past year.*
2. *This could be due to poor dissemination of planned outages by ECG, low attention to this information by customers, and/or a large share of outages being unplanned.*
3. *Most customers that do report ever being notified about outages in advance find out the same day (53%) or the day before (38%).*
4. *Neighbors are the main source of information (67% of respondents), indicating that advance notice of outages usually spreads by word of mouth. Around one-third of respondents find out about outages on the radio.*
5. *Respondents are nearly evenly split on their perspectives about whether Dumsor is back, with 53% having a more negative attitude toward current electricity quality.*
6. *Reliability experiences in the past 30 days explain a small share of perspectives on electricity quality. Being aware of more outages in advance is not associated with different attitudes about electricity.*

Figure 43 illustrates that a large majority of respondents report not being aware of any outages ahead of time in the past year, with no differences between businesses and households. Just 13% of respondents report being aware of any outages in advance. Among these, the median respondent reports being aware of 10% of outages in advance. This low level of advance outage awareness may reflect three factors. First, ECG may not be successfully disseminating outage plans, either by not disseminating them soon enough or by not sharing the information in ways that are broadly accessible.

Access to the internet, and to social media in particular (used by ECG to disseminate outage plans), may be a barrier for many customers. Second, customers may not be attentive to ECG outage information, either by not seeking it out in places they know it is available, or by not recalling it after having accessed it. The fact that so many respondents report never being aware of outages suggests this factor accounts for at least some of the low levels. Finally, most outages are likely not planned and thus not announced in advance. Though the situational reports suggest around half of feeder-level outages are planned in advance, it is not clear what share of outages customers experience are due to feeder level outages as opposed to issues in the local LV network.

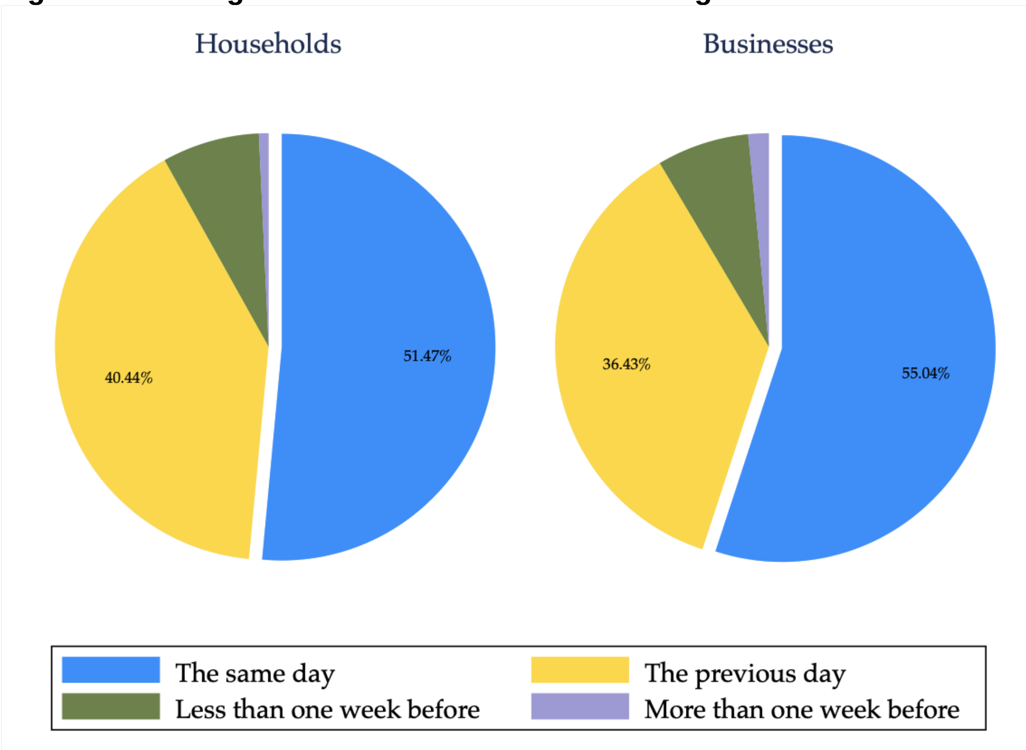
Advance notification about planned outages will only benefit customers if it gives them enough time to adjust their plans as necessary. Over half of households and businesses that report ever being aware of an outage in advance report finding out about it the same day (51% and 55% respectively), with the bulk of the remainder finding out the day before (Figure 44). While this may be enough time for some adjustments, customers in general have a short window between finding out about an outage and having that outage occur.

Figure 43. Distribution of Advance Outage Awareness



Source: Baseline survey.

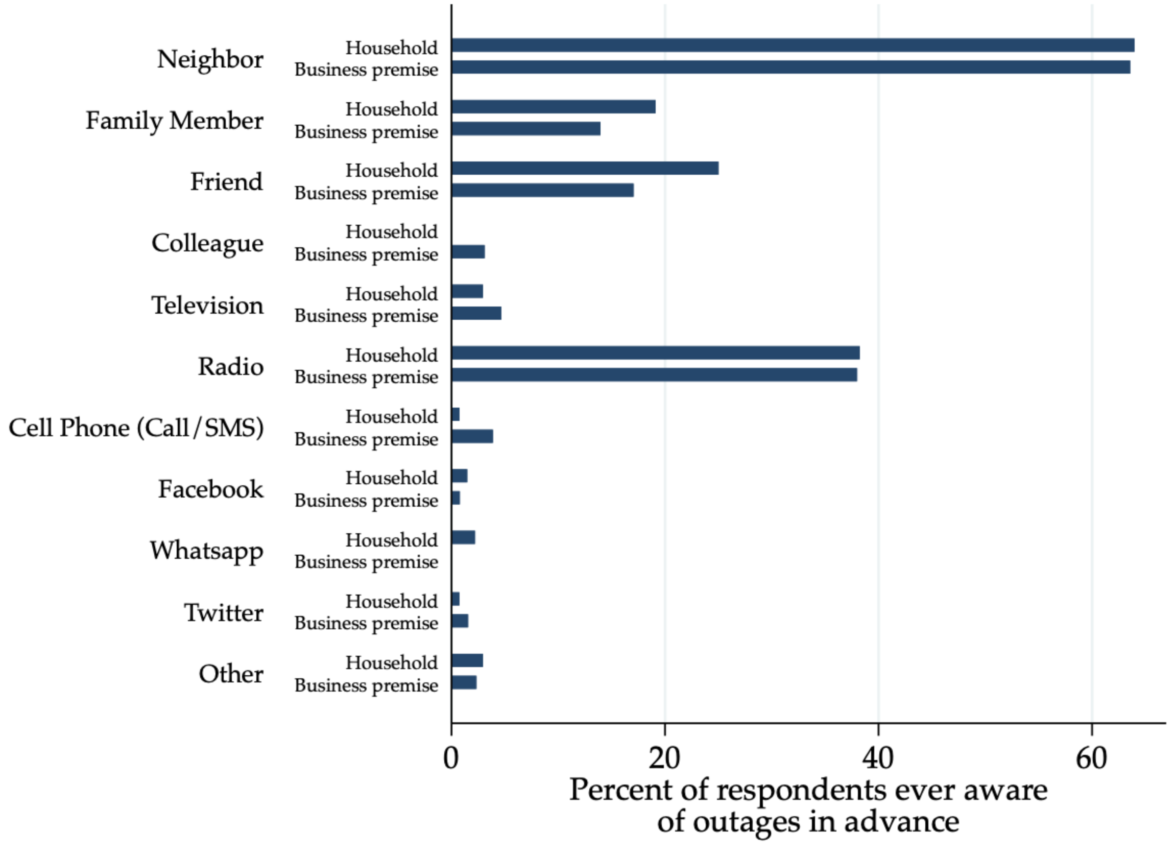
Figure 44. Timing of Notification for Planned Outages



Source: Baseline survey.

Households and businesses report using the same sources of information to find out about planned outages, though households are slightly more likely to hear about outages from a family member or friend (Figure 45). Around two-thirds of respondents that were ever notified about an outage in advance found out from a neighbor. Family members and friends are the third and fourth most common sources. Altogether, this indicates that much of the information about planned outages is spread by word of mouth rather than sought out specifically. The second-most common source is radio announcements, reported by 38% of respondents. Efforts by ECG to disseminate outage information online do not seem to be reaching respondents.

Figure 45. Sources of Information About Planned Outages



Source: Baseline survey.

Table 16 presents correlates of the share of outages respondents were aware of in advance over the past year. Respondents that experience more outage hours are less likely to be aware of outages in advance, suggesting that customers experiencing more outages are largely facing outages that stem from issues in the LV network. Households are aware of slightly more outages in advance than businesses. Respondents with a generator are aware of around 4 percentage points more of their outages ahead of time, perhaps because they depend more on electricity and therefore are more invested in obtaining this information. On the other hand, respondents with more appliance types are less aware of outages in advance, despite the fact that they might benefit more from early notification. There is no difference by whether respondents are in LB treatment sites.

Table 16. Correlates of Outage Awareness

	(1)	(2)	(3)
Total outage duration in past 30 days (hrs)	-0.008*	-0.008**	-0.009**
	(0.004)	(0.004)	(0.004)
Average low voltage hours per day in past 30 days	0.038	0.036	0.040
	(0.076)	(0.077)	(0.073)
Respondent is a household only		1.232*	1.270**
		(0.643)	(0.602)
Has generator		4.632*	4.346*
		(2.623)	(2.562)
Total count of appliance types owned		-0.059	-0.254*
		(0.114)	(0.134)
LB Treatment		0.339	0.409
		(0.686)	(0.691)
Outcome Mean	2.904	2.904	2.910
Observations	1989	1989	1985
Additional Controls	No	No	Yes

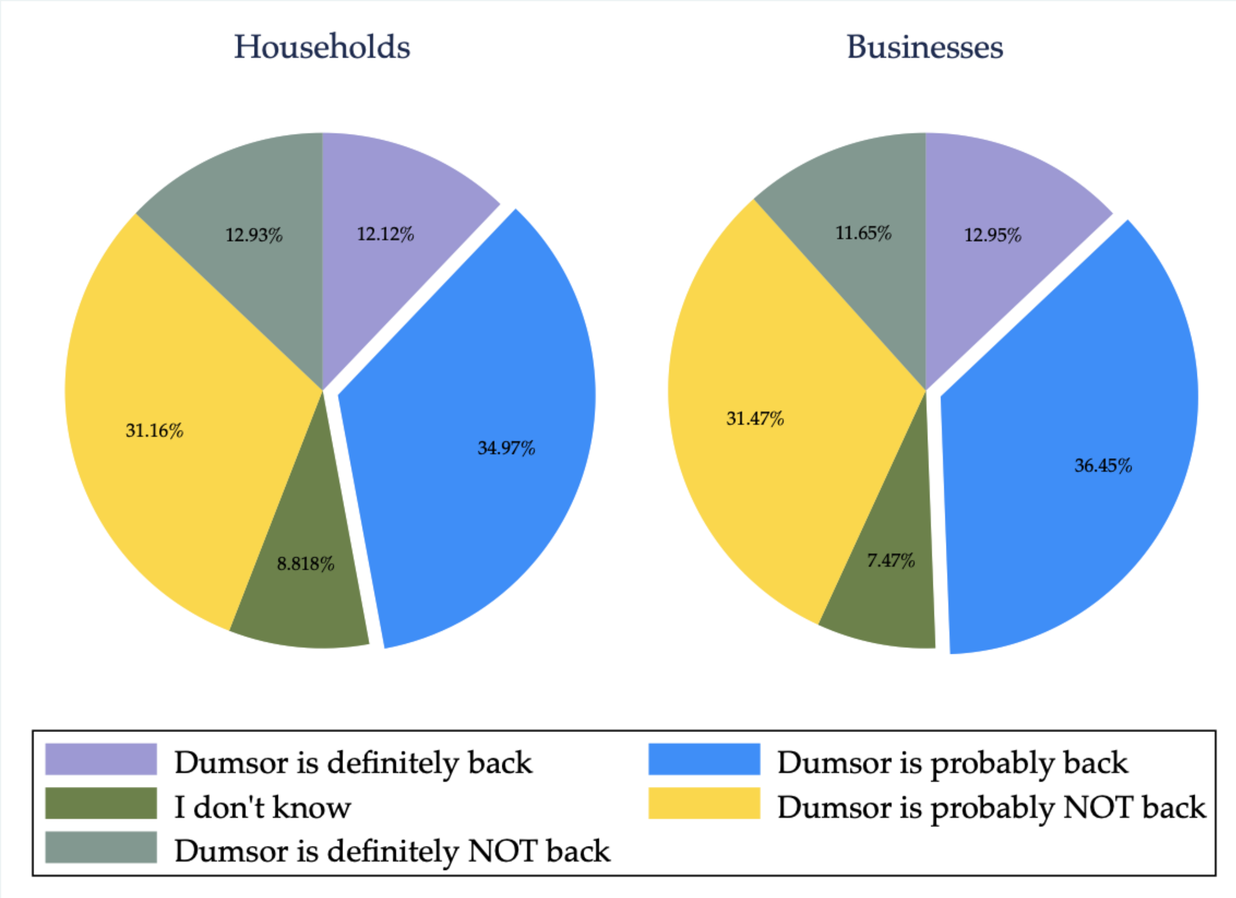
Source: Baseline survey.
Notes: The outcome in all three columns is the percentage of outages in the past year that the respondent was aware of in advance. Rows report estimated coefficients for particular variables from regressions of the outcome on a set of variables. Standard errors clustered at the site level are included in parentheses. Asterisks indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Additional controls included in column (3) but not displayed in the output for simplicity include respondent age, sex, and level of education, dummies for whether the tenants own or rent the premises, a dummy for whether the tenants pay a landlord for electricity or manage their meter directly, the count of mobile phones owned at the premises, and the latitude and longitude for the survey site centroid.

3.8.2 Perspectives on Dumsor

We asked respondents to give their perspectives on electricity quality through the following question: "*On a scale of 1-5, where 1 is "definitely back" and 5 is "definitely not back", how likely do you think it is that Dumsor is back?"* Respondents who answer that Dumsor is "definitely back" believe that electricity reliability is very poor and see parallels to the levels of reliability experienced during the Dumsor crisis. Respondents who answer that Dumsor is "definitely not back" have a more positive perspective of current electricity reliability. A higher value on the scale from 1 to 5 therefore indicates that respondents feel more positively about their current quality of electricity, with a 3 indicating neutrality.

Figure 46 shows the shares of households and businesses with different perspectives on Dumsor at baseline. For both, the most common response (35% of households and 36% of businesses) is that "Dumsor is probably back," indicating somewhat negative perspectives about electricity reliability. The next most common response, however, is that "Dumsor is probably NOT back" (31% of both households and businesses). Among those not responding "I don't know," 53% have negative perspectives about electricity quality, indicating that customers are nearly evenly split in their attitudes.

Figure 46. Respondent Perspectives on Dumsor



Source: Baseline survey.

Table 17 analyzes the correlates of Dumsor perspectives, where the outcome is again on a scale from 1 to 5 and a higher value indicates more positive attitudes about electricity quality. As expected, measures of electricity reliability are strongly correlated with Dumsor perspectives. An additional hour of outages in the past 30 days reduces the rating of electricity quality by 0.003, and an additional hour of low voltage hours per day reduces the rating by 0.025. Thus, a respondent with the mean outages and daily low voltage hours in the past 30 days would have an electricity quality rating 0.16 points lower than a respondent with perfectly reliable electricity, holding everything else constant. This is not a very large effect, and suggests that perspectives of electricity quality are likely based on reliability experiences over a longer time period than the last 30 days.

Table 17. Correlates of Dumsor Perspectives

	(1)	*(2)*	*(3)*
Percent of outages in past year aware of in advance	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)
Total outage duration in past 30 days (hrs)	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Average low voltage hours per day in past 30 days	-0.025***	-0.025***	-0.022***
	(0.008)	(0.008)	(0.009)
Respondent is a household only		0.068	0.043
		(0.057)	(0.062)
Has generator		-0.039	-0.149
		(0.158)	(0.162)
Total count of appliance types owned		-0.005	-0.004
		(0.012)	(0.015)
LB Treatment		0.052	0.042
		(0.085)	(0.080)
Outcome Mean	2.952	2.952	2.952
Observations	1989	1989	1985
Additional Controls	No	No	Yes

Source: Baseline survey.
Notes: The outcome in all three columns is the respondent's perspective about Dumsor, rated on a scale from 1 (Dumsor is definitely back) to 5 (Dumsor is definitely not back). Larger values therefore represent more positive perspectives about Dumsor. Rows report estimated coefficients for particular variables from regressions of the outcome on a set of variables. Standard errors clustered at the site level are included in parentheses. Asterisks indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Additional controls included in column (3) but not displayed in the output for simplicity include respondent age, sex, and level of education, dummies for whether the tenants own or rent the premises, a dummy for whether the tenants pay a landlord for electricity or manage their meter directly, the count of mobile phones owned at the premises, and the latitude and longitude for the survey site centroid.

No other observed characteristics are significantly associated with Dumsor perspectives. In particular, being aware of more outages in advance does not improve perspectives of electricity quality. Of course, being aware of a greater share of outages in advance could have two effects. First, it could draw attention to the level of outages, which could lead to negative electricity perceptions. But on the other hand, being aware of more outages in advance could mean there are fewer unexpected outages, meaning the quality of electricity is better and leading to positive electricity perceptions. The endline survey may include additional questions asking directly about perspectives of the utility and advance outage notifications to evaluate this.

4. Risks to Program Logic and Evaluation Strategy and Concluding Remarks

In this section, we discuss potential risks to the program logic and evaluation strategy for the Compact's line bifurcation intervention in light of the baseline findings.

4.1 Line Bifurcation Construction

An initial concern for the LB evaluation approach was that construction might not follow the initial selection of construction sites. Before the start of the baseline surveys, the PMC shared a set of updated line bifurcation injection sites, which allowed us to revise the list of treatment and control sites and to adjust the deployment GridWatch devices ahead of construction. The final set of 76 treatment and 75 control sites reflects the PMC's updated set of LB injection sites. We have been working with the PMC to verify that construction adheres to the list of planned line bifurcation injection sites, and that no injections take place in the sites we have selected as controls. The PMC has also shared administrative data on their construction progress across Achimota, Dansoman and Kaneshie.

In addition, we have conducted construction monitoring surveys to independently monitor construction progress and equipment installation by the PMC and the contractors conducting the LV bifurcation work. As part of these surveys, field officers visit treatment sites to verify the existence of a new transformer, and visit control sites to verify that no new transformer has been installed. Reassuringly, there appears to be close alignment between our own construction monitoring data and the construction progress information provided by the PMC thus far.

It is possible that additional construction will take place at what were supposed to be control sites by the time of the endline survey. We will therefore continue our construction monitoring survey at that time. If compliance turns out to be a concern, this should still not pose a risk to the evaluation strategy, as we can employ an instrumental variable approach where being on the initial list is used as an instrument for whether there was construction at that site. As long as the location of construction still aligns with treatment assignment in the majority of cases, we will be able to obtain an accurate estimate of the impact of line bifurcation on power quality.

4.2 No Change in Reliability or Perceptions of Reliability

The theory of change is that line bifurcation injections will lead to improved power reliability and quality, which in turn will lead to improved electricity usage, which will improve economic outcomes. If the first outcome—improved power quality—is not achieved, then improvements in the economic outcomes of the program logic illustrated in Figure 1 are unlikely.

It is too soon to determine whether power quality has improved in treatment sites relative to control sites since LB construction was completed, but in Section 3.2 we present preliminary data from GridWatch devices suggesting that reliability may have started to improve in treatment sites in the first few months post-construction. We also show that reliability is relatively poor at baseline: around 40 hours of electricity outages and 45 hours of bad voltage per month. This indicates that there is a lot of room for improvement following LB construction.

A related risk is that, conditional on there being improvements in electricity quality, beneficiaries may not realize that power quality is improving. Due to the lack of awareness of improvement of power, households and firms may not meaningfully change their energy use and invest in better appliances or machinery. Fortunately, awareness of improved reliability is not necessary for the majority of the long-term outcomes we consider under Stage 3 of the program logic. For example, electricity consumption may increase simply because electricity is available for more hours per day, while business revenues may increase by being able to operate more consistently with fewer disruptions. Awareness of the improvement is not required in either case. However, larger changes in energy use, electricity consumption, and business and household outcomes are more likely to be observed if customers perceive improvements in electricity reliability. We will investigate our respondents' awareness in our endline surveys.

4.3 Low Statistical Power

Another potential challenge to the line bifurcation evaluation is low statistical power if reliability improvements are small. When compared with the significant periods of power outages during the Dumsor period, the changes in outages brought about by line bifurcation may be imperceptible to most customers, especially in the short run. This relates to Stage 2 of the program logic (Figure 1). At this time, we do not have sufficient data post-construction to estimate the change in reliability. The GridWatch devices are powered to detect reduction of 3.34 hours of outages per month or larger, which is line with expectations for the LB intervention.

A greater concern is the ability to detect significant changes in long-term outcome variables, as these will only be affected by the LB intervention to the extent that this intervention improves electricity reliability and to the extent that improved reliability affects these outcomes. Table 18 summarize power calculations based on baseline survey data for key outcomes of interest. Based on the baseline mean and standard deviation (SD) for these variables, the minimum detectable effect (MDE) is the smallest impact of the LB intervention that could be statistically distinguished from a null effect with a 95% confidence level given the sample size. Any level of impact below the MDE will not be detected at this significance level. MDEs are mechanically lower if we apply a significance level of 0.10, so some smaller effect sizes will be detectable at this lower level of significance.

For each variable in Table 18, the MDE is in the units of that variable. For dummy variables, they represent changes in the probability that the variable is equal to 1. For comparability across variables, the table also shows what the MDE represents in terms of a proportional change in the outcome. For example, there is sufficient power with this sample size to detect anything greater than a 12% change in monthly electricity spending, but nothing below that.

These power calculations are based on a power level of 0.8, meaning the probability of falsely failing to reject the null hypothesis is 20%, and a significance level of 0.05. This is standard practice when performing power calculations for impact evaluations.

These MDEs have implications for what the effect of LB treatment on reliability and the effect of reliability on an outcome must be to detect significant effects of LB treatment on the outcome. Suppose LB treatment reduces outage hours by 20%. An MDE of 10% for electricity spending means that a 1% decrease in outage hours must increase electricity spending by at least 0.5% for the effect of LB treatment on electricity spending to be detected. The larger the impact of LB treatment on reliability outcomes, the smaller the effects of those outcomes on long-term socioeconomic outcomes of interest can be while still being statistically detectable.

Table 18. Power Calculations: Minimum Detectable Effect (MDE) for Key Outcomes of Interest

	N	Baseline Mean	SD	MDE	Proportional Change
Reliability					
Total outage duration in past 30 days (hours)	2002	39.18	47.71	5.98	15.26%
Average bad voltage hours per day in past 30 days	2002	1.55	3.10	0.39	25.16%
Importance of electricity as business obstacle (1-5)	1004	3.87	0.99	0.18	4.65%
Monthly willingness to pay for perfectly reliable electricity (GHS)	2002	20.41	31.44	3.94	19.30%
Energy use					
Monthly electricity spending (GHS)	2002	104.09	99.85	12.51	12.02%
Monthly spending on alternative fuels (GHS)	2002	39.60	48.71	6.10	15.40%
Count of mobile phones	2002	2.15	0.63	0.20	9.30%
Any television (=1)	2002	0.82	0.68	0.09	10.98%
Any refrigerator/freezer (=1)	2002	0.79	0.79	0.10	12.66%
Any stabilizer (=1)	2002	0.16	0.43	0.05	31.25%
Any generator (=1)	2002	0.04	0.19	0.02	50.00%
Any alternative energy source (=1)	2002	0.05	0.21	0.03	60.00%
Business outcomes					
Number of business workers	1004	1.99	2.11	0.37	18.59%
Business revenues in the past month (GHS)	1004	2570.05	3874.92	685.88	26.69%
Business profits in past month (GHS)	1004	649.12	919.75	162.80	25.08%

Source: Baseline survey.
Note: MDEs are estimated based on a power level of 0.8 (the probability of falsely failing to reject the null hypothesis is 20%) and a significance level of 0.05. MDE units are the same as that of the variable in question.

4.5 Duration of Exposure Period and Reliability Improvements

Line bifurcation construction activities were completed in the three districts of Achimota, Dansoman, and Kaneshie in late March to early April 2021. The baseline survey was conducted in March-April 2021, and the endline will take place from July-September 2022. The LB treatment exposure period for sample households and businesses will therefore be between 13-17 months.

Improvements in electricity reliability from line bifurcation transformer injections should be immediate. A new transformer injection should reduce the electricity load on the surrounding LV network and reduce the length of service or distance to customers, producing the initial outputs of the LB intervention program logic. As a result, an exposure period of a little over one year should be sufficient time to observe changes in most outcome variables of interest. An exception is that certain long-term socioeconomic outcomes may take longer to respond to improvements in electricity reliability. For example, investment in electric appliances may be unlikely to change by the end of the exposure period. Customers may not be convinced within one year that improvements in reliability will be sustained, and even if they are it may take time for them to accumulate enough savings to invest in new appliances.

A separate concern is that reliability improvements may not be sustained by the end of the exposure period. If initial improvements in reliability due to the reduced load on the network cause customers to adopt more appliances and increase electricity consumption, this could increase the network load and offset the gains from the LB injections, causing electricity reliability to revert to baseline levels at the end of the exposure period. This scenario appears unlikely, as load reductions due to transformer injections should be fairly large, meaning electricity consumption would have to increase significantly to offset them. Even in this case, the high frequency of GridWatch data would reveal this pattern over time, and these data could be matched with endline survey data about when beneficiaries adopted new appliances.

4.5 Concluding Remarks

Baseline findings indicate that levels and trends of electricity reliability were similar prior to the LB intervention in treatment and control sites and that household and business survey respondents were similar on observable characteristics. This indicates that the DD evaluation strategy should successfully identify impacts of the LB intervention on electricity reliability in the short-term and on household and business socioeconomic outcomes in the long-term.

Initial data post-construction from GridWatch devices suggest that reliability may be improving in treatment sites, but it is too soon to tell whether any improvements are significant. Baseline data show relatively high levels of outage and bad voltage hours, such that injections should lead to measurable improvements.

A benefit of the line bifurcation intervention design is that customers do not need to perceive any reliability improvements in order to experience long-term benefits. Electricity consumption may increase simply because electricity is available for more hours per day, while business revenues may increase by being able to operate with fewer disruptions. Damages from bad voltage and associated costs should also fall. Awareness of the improvement is not required in any of these cases. However, larger changes in energy use, electricity consumption, and business and household outcomes are more likely to be observed if customers perceive improvements in electricity reliability and adopt more electric appliances as a result. The endline surveys will collect information on respondents' awareness of any changes in reliability.

The baseline sample of households appears to be fairly representative of households in Accra, excluding high-income households. Findings from this evaluation could therefore be used to understand how electricity reliability improvements could affect urban households in Accra and across Ghana more generally. Sampled business are predominantly small and overrepresented in industries that do not rely heavily on electricity. LB evaluation findings from the business sample are therefore unlikely to reflect how businesses in Accra in general would be affected by improved electricity reliability, but more indicative of impacts on small owner-operated businesses. Given that the baseline sample of businesses is likely less reliant on electricity than the broader population of businesses, estimated impacts on business could be considered as lower bounds for the impacts that businesses would experience more generally.

Baseline data on businesses' and households' coping mechanisms for reliability issues suggest potentially large benefits from any reduction in outages. Few households or businesses have generators or other alternatives to electricity, so many businesses stop their activities when an outage occurs. LB improvements could therefore lead to significant increases in electricity consumption and appliance use even if use of alternative energy sources does not fall. Businesses could benefit from fewer work disruptions, though benefits may be small for businesses that do not rely on electricity for their operations. Those that do, such as clothing manufacture and repair businesses, could see increased revenues and profits. Savings from the costs of repairing or replacing appliances damaged by voltage fluctuations may also be significant.

Businesses that perceive an increase in reliability could respond in a variety of ways. Assuming reliability improves productivity, this could spur increases in employment, although changes in labor use are less likely for businesses in the sample that are owner-operated with just 1 or 2 employees. The potential effect of improved electricity reliability on business hours is ambiguous. Businesses are typically open for 12 hours per day, from 8am to 8pm. Businesses might work longer hours if these hours are more productive and profits increase, or they might work fewer hours if they can reach target output or revenue levels in a shorter amount of time. Businesses might also be more likely to stay open at night with more reliable electric lighting.

5. Administrative

5.1 Data Access, Privacy and Documentation Plan

5.1.1 Summary of Institutional Review Board Requirements and Clearances

All survey instruments, consent forms, and data collection protocols for this evaluation were submitted for review by the Committee for the Protection of Human Subjects (CPHS) which is the Institutional Review Board (IRB) for the University of California, Berkeley (UCB) and the University of Ghana ISSER [add name of ISSER IRB board]. All activities have been approved prior to implementation and we foresee no issues continuing this going forward.

5.1.2 Data Protection

At a high level, all data collected was encrypted both in flight (*i.e.,* during any network transmission) and at rest (*i.e.,* persistent storage). All data handling procedures were in compliance with all appropriate Federal and UCB IRB regulations. Specific data protection methods are outlined below.

Surveyors in Ghana have collected data using encrypted tablets on a secure Open Data Kit-based platform, namely SurveyCTO. The tablets were encrypted with passwords to prevent a third party from accessing the data. Each Surveyor sent the data to the secure SurveyCTO server at the end of each day.

To maintain confidentiality, surveyors were prohibited from using these tablets for purposes outside the survey. Data uploaded to the SurveyCTO server was encrypted automatically. Data downloaded from the SurveyCTO server was stored in password-protected locations on the researchers' computers. Any hard copies used in the surveying activities, were stored in locked cabinets. For security purposes, all data were kept in encrypted files.

Any sensitive data that were collected and needed to be shared among the researchers were securely stored within a standalone encryption container, such as a Cryptomator vault, *before* being uploaded to any secure cloud-based storage service such as Box. These fully encrypted containers encrypt both filenames and their contents. Any fully encrypted container synced to cloud folders was shared only amongst immediate members of the evaluation team. In addition to their cloud service credentials, these team members were only able to decrypt the container via a secure randomly generated passphrase shared via a password management tool such as LastPass. Access to the underlying data thus requires both a protocol user's Box and LastPass account credential to access the encrypted file share and its unlocking password, respectively. Local working copies of the sensitive data may then be synced to researchers' computers, where they were secured by user passwords and disk-level encryption.

If raw audio files were collected via the PowerWatch sensors (for purposes of detecting AC mains "hum"), these were stored on the SD card of PowerWatch sensors over the course of the deployment. When PowerWatch is collected, the files will be removed from the SD cards and placed in an encrypted database. The SD cards will then be erased. Any raw audio files captured by the GridWatch app (for the same power presence detection reasons) will be stored on the phone of the GridWatch participants. As with all data above, these files will be encrypted both in flight and at rest. These files are removed when the app is uninstalled at the end of the study.

5.1.3 Preparing Data Files for Access, Privacy and Documentation

The privacy of every participant in the data collection process was treated with the utmost respect and care throughout the evaluation. Datasets provided follow both IRB and MCC Data Documentation and

Anonymization Requirements, including those specified in the MCC Evaluation Microdata Documentation and De-Identification Guidelines. In keeping with the spirit of MCC's emphasis on transparency, findings and data that meet the aforementioned privacy requirements will be published and shared with the broader development research and donor communities, as outlined in the dissemination plan below. Properly anonymized and privacy-protected datasets will be released within 6 months of their respective final reports, after iterative rounds of consultation with the MCC Disclosure Review Board. Household- and firm-level data will require low levels of effort to prepare for publication and release. Identifiers will be removed from the private identifiable information. After such removal, the information can be published and used for future research studies or distributed to other investigators. Data collected through the DumsorWatch App and PowerWatch devices are particularly useful to researchers when mapped to geographic areas, and anonymized versions of the data (without any locational information) will be less productive to other researchers. The research team will explore ways of editing or anonymizing the data that is in line with IRB confidentiality and anonymity requirements but that will still prove useful to outside researchers. However, once a protocol is agreed upon, this task will likely be easy to streamline due to the clean and highly formatted nature of the data collected. This task will therefore likely require medium-level levels of effort.

Identifiers were removed from the data upon download and stored separately. Responses were assigned a code number, and the list connecting personally identifiable information with this number were kept secure and will be destroyed five years after the completion of the study. Identifiable and coded information was secured via both password protection and encryption on the surveyors' tablets, in the SurveyCTO survey server and on researchers' computers. All identifiers will be coded using a master list. This list was stored in a password protected and encrypted database on a server and was made available only to members of the study team. It will be kept for a period of five years after study completion, after which it will be destroyed.

5.2 Dissemination Plan

In November 2017, we met with senior members of the Ministry of Energy, including the Acting Chief Director and the Director for Generation and Transmission. Both expressed frustration with the poor quality and credibility of the electricity reliability data that they currently use to make key investment and project decisions. They emphasized a need for higher quality data, especially when paired with rigorous socioeconomic research, to better understand the economic impacts of ECG's investments in Ghana's electricity infrastructure. We plan to continue our engagement with senior management at the Ministry to ensure dissemination of results with key decision makers, so that our findings can lead directly to improvements in ECG investments and operations.

Our close and extensive collaboration with Kenya Power over the past 2 years has revealed a similar urgency to improve the quality of data that policymakers use to make key operations and infrastructure investments decisions in Kenya. This is reflected in the fact that Kenya Power and GridWatch are currently working to integrate GridWatch sensing into Kenya Power's mobile app, with the eventual goal to use the resultant data stream as an input into their operational systems.

We also intend to engage citizens and disseminate our research to members of civil society. On our research trip in November 2017, we engaged with thought leaders in the non-governmental sector (including the Executive Directors of KITE and ACEP), as well as senior academics at GIMPA and the University of Ghana. These stakeholders all agreed on the importance of enhancing independent data collection as a way to hold government players more accountable and improve their understanding of the socioeconomic and distributional effects of poor reliability in the Ghanaian context. We also met with Kobina Aidoo, primary author of the Dumsor Report, a citizen initiative that distributed information about outages to citizens during the Dumsor crisis via social media outlets (Briggs and Aidoo, 2018). As the Dumsor crisis grew in severity, public interest in the Dumsor Report grew rapidly, and Kobina's network of social media and civil society contacts enabled the report to reach widespread prominence. We feel confident that we will be able to use these established channels to disseminate our data and findings to the general public.

After the submission and review of the baseline report Q1 2022, we will be presenting the Evaluation Baseline Report with an interim update on the Line Bifurcation Evaluation and Priority Feeder analyses to MCC and MiDA stakeholders in Accra, Ghana.

5.3 Evaluation Team Roles and Responsibilities

The first principal investigator (PI) for this project is Professor Catherine Wolfram, the Cora Jane Flood Professor of Business Administration at the Haas School of Business, University of California, Berkeley. Professor Wolfram is a Research Affiliate at the Energy Institute at Haas and the Program Director of the National Bureau of Economic Research's Environment and Energy Economics. Catherine is currently on leave from UC Berkeley serving as Deputy Assistant Secretary for Climate & Energy Economics in the U.S. Department of the Treasury. Catherine's role focuses on conducting socioeconomic research and impact evaluation of a number of electricity interventions happening in Accra.

The second PI is Prabal Dutta, an Associate Professor in Electrical Engineering and Computer Sciences at University of California, Berkeley. He has been recognized with an NSF CAREER award, an Alfred P. Sloan Research Fellowship, an Intel Early Career Award, and a Popular Science Magazine Brilliant Ten Award. Prabal's role focuses on contributing to the high-level architecture and design of the technology used in the research project.

Steve Puller, the PERC Professor of Free Enterprise in the Department of Economics at Texas A&M University, has extensive research experience studying the electricity sector in both developed and developing countries. Steve's role in the project is focused on the implementation of the priority feeder and the LV bifurcation differences-in-differences, the assembly and analysis of the household-level and firm-level surveys, estimating the impact of reliability on socioeconomic outcomes, and writing research reports.

Professor Jay Taneja is an Assistant Professor in Electrical and Computer Engineering at the University of Massachusetts Amherst. Jay will oversee the technical components of the project, and will be a primary contact in collaborations with employees of the utility in Ghana.

Matt Podolsky, Managing Director of the UCB Technology and Infrastructure for Emerging Regions group and Associate Director for Data Analytics at DIL, is serving as the data collection expert and co-fulfilling senior engineering duties. Matt will be responsible for the management of the technology development and deployment (fixed sensors, GridWatch app, and data collection system).

Karen Notsund, Associate Director at the Energy Institute at Haas, (1) assists the PIs and team with reports and dissemination of results, (2) manages deliverables and HR for Energy Institute personnel, and (3) coordinates efforts for this project and its intersection with other funding sources for different phases of this project.

Noah Klugman, a Ph.D. candidate in Computer Science and Engineering at UCB, is a Graduate Student Researcher on the project. Noah is the first author on the original GridWatch paper and is the lead developer of the suite of technologies deployed in this project. Under the supervision of Professor Dutta, Noah will be responsible for implementing the GridWatch app, the PowerWatch fixed sensors, and the automatic incentive payment schemes. Noah, along with co-PI Prabal Dutta and UCB Graduate Student Researcher Josh Adkins, has founded nLine Inc. nLine Inc. is the company that has designed and manufactured the PowerWatch sensors and Data Visualization System.

Susanna Berkouwer, Assistant Professor of Business Economics & Public Policy at the Wharton School at the University of Pennsylvania, specializes in microeconomics in the context of environment, energy, and climate in developing countries. Susanna's role in the project is focused on the implementation of the priority feeder and the LV bifurcation regression, discontinuity designs, the assembly and analysis of the household-level and firm-level surveys, and estimating the impact of reliability on socioeconomic outcomes, and writing research reports.

Geetika Pandya, a graduate of UCB's Master of Development Practice program, is the Project Manager for the evaluation. Geetika is responsible for providing project management support, and assisting in the design and implementation of the research on the ground. Geetika also interfaces with key stakeholders, prepares progress reports and budgets, and ensures smooth functioning of the team.

Pierre Biscaye, a Ph.D. candidate in the Department of Agricultural and Resource Economics at UCB, is a Graduate Student Researcher for the GridWatch project. Pierre's role is to oversee the design and implementation of field activities and surveys in Ghana and to conduct the socioeconomic analyses for the impact evaluation.

5.4 References

Abeberese, A. B., C. G. Ackah, P. O. Asuming, 2017. “How did the 2012-2015 power crisis affect small and medium manufacturing firms in Ghana?” *International Growth Centre*. Policy Brief #33305.

Albert, J., S. Alikhan, L. Etter, M. Jeuland, and A. Wyatt, 2014. “Jordan compact – Water network, wastewater network, and As-Samra expansion projects.” *Impact Evaluation Design Report.*

Allcott, H. and A. Collard-Wexler, S. D. O’Connell, 2016. “How Do Electricity Shortages Affect Industry? Evidence from India.” *American Economic Review.* 106 (3): 587-624.

Briggs, R. and K. Aidoo, 2018. “Underpowered: Rolling blackouts in Africa disproportionately hurt the poor.” *African Studies Review*, forthcoming.

De Mel, S., D. McKenzie, & C. Woodruff, 2008. “Returns to capital in microenterprises: evidence from a field experiment. “*The Quarterly Journal of Economics*, 123(4), 1329-1372.

Dzansi, J., S. L. Puller, B. Street, B. Yebuah-Dwamena, 2018. “The Vicious Circle of Blackouts and Revenue Collection: Evidence from Ghana.” *International Growth Centre.* Working paper E-89457-GHA-1.

Fisher-Vanden, K., E. Mansur, and Q. Wang, 2015. "Electricity Shortages and Firm Productivity: Evidence from China's Industrial Firms." *Journal of Development Economics*. 114: 172-188.

Hardy, M. and J. McCasland, 2019. “Lights Off, Lights On: The Effects of Electricity Shortages in Small Firms in Ghana.” *Working Paper.*

Lee, D. S. and T. Lemieux, 2010. “Regression Discontinuity Designs in Economics.” *Journal of Economic Literature*, 48(2): 281-355.

World Bank Group, 2013. “Ghana Enterprise Survey.”

Annexes

Annex A: Priority Feeder Analysis

PRIORITY FEEDER RESULTs: THE SOCIOECONOMIC IMPACTS of DUMSOR OUTAGES[1]

Contents

[1]This research has IRB approval from UC Berkeley. We thank Simon Bawakyillenuo, Ralph Sam, and their col-leagues at the Institute of Statistical, Social and Economic Research at the University of Ghana for their superb implementation of field activities. A Pre-Analysis Plan for this research was submi1ed to 3ie's Registry for International Development Impact Evaluation https://ridie.3ieimpact.org/index.php?r=search/detailView&id=928

1 Introduction

There is a widespread belief among policy makers, development agencies and researchers that access to reliable electricity services is a keystone for economic development and poverty reduction. Electrification holds a central role in both the World Bank and UN directives, but the early goals of targeting electricity access alone is now being complimented by promoting consistent access to reliable and dependable electricity.

In the latest UN Sustainable Development goals sets a goal to a1ain universal access to ”affordable, reliable and modern” energy services (UN General Assembly,2016). This is encoded by suggesting there are 5 tiers of electricity access–ranging from tier-1, which includes task lighting, radio and phone charging, to tier-5, which is defined by access to modern and continuous use of electric appliances including air conditioning. As such, while the conversation is still centered around electricity access, experts are beginning to focus on the topic of electricity dependability, reliability and the level of service simultaneous with access.

Even though grid connected consumers have the potential to reach the highest tier of electricity access–that which supports continuous appliances usage and air conditioning–without predictable and reliable electricity grid electricity, they may not reach the higher tiers of access even if they are connected to the national grid.

Anecdotally, we know that frequent outages constrain the economic well-being of households and small businesses by reducing the benefits from and discouraging investments in welfare-improving appliances (such as fans, refrigerators, or income-generating assets like sewing machines). In the face of unreliable electricity services, some customers make large investments in substitutes for high-quality grid electricity (such as generators), which potentially crowds out other productive investments.

In this annex, we report the results of our work analyzing the impact of power quality on long-term outcomes. In tandem with our line bifurcation analysis, this will allow us to more accurately recover the long-term impacts of grid investments on economics outcomes using multiple methods and se1ings.

Specifically, we evaluate the socioeconomic impacts to households and businesses of unreliable electricity in the context of Ghana’s 2012-2016 electricity crisis. This period of high and persistent outages offers a nice se1ing for study—as in the urban areas of Ghana more than 90% of households are already connected to the national electric grid. In these se1ings, the primary issue is the energy quality and grid reliability rather than access to electricity. Between 2012 and 2016, persistent power shortages in Ghana lead to rolling blackouts which negatively affected Ghana’s economy and gave rise to the term “Dumsor,” meaning “lights off-on” in the local Akan language. According to the World Bank Enterprise Surveys in 2013, 61.2% of firms in Ghana cited electricity reliability as a major constraint, with firms reporting an average of over 700 hours of outages annually (The World Bank,2013). For comparison, American firms face on average of 1.5 hours of outage per year. At the peak of the Dumsor crisis period in 2015, broad parts of Ghana experienced 12 hour of outages in every 48 hour period, on average, as part of nation-wide load-shedding efforts to balance the national grid.

The load shedding directive in Ghana was intended to be fair and equal, but also takes into account critical load centers that were prioritized to receive supply even in face of persistent electricity shortages. As such, we can leverage these spatial discontinuities in the network to casually evaluate the impacts of electricity supply during the Dumsor period via a natural experiment. During Dumsor, some feeders were designated as exempt from load shedding status as they provided electricity to key infrastructure–such as hospitals, police stations, military barracks or other important customers. These feeders received priority for available electricity supply based on this consideration. However, these feeders also serve other households and businesses that the utility does not intend to prioritize directly and which may be far away from protected load center, like a hospital. Therefore, some households and small businesses may also receive improved electricity services since they are connected to a feeder with "priority" status, even though ECG does not intended to prioritize their access. Thus if some customers happen to be serviced by an exempt feeder, they will receive be1er power quality as a direct consequence of simply being connected to the same line as an important load center.

The key to our identification strategy for this natural experiment is that the prioritization of some exempt feeders leads to exogenous variation in power quality and load shedding for otherwise statistically indistinguishable households and firms. We construct a set of households and businesses–some of which are connected to priority feeders and others who are connected to ordinary feeders based on the pre-existing grid configuration–that are statistically equivalent to evaluate the causal impacts of electricity reliability. We show that this se1ing provides exogenous variation in the quality of the electricity supply we can use to evaluate the impacts of power quality, not just access. We accomplish this task using novel spatial data for the electricity network in Accra and historical data on outages by feeder during the Dumsor crisis period. We use these data to identify neighboring "treatment" (*i.e.* those connected to priority feeders) and "control" (*i.e.* those connected to non-priority feeders) areas that are comparable along socioeconomic dimensions. In each of these areas, we surveyed households and businesses about their electricity experiences and perspectives, appliance ownership, recall about the Dumsor period, and their household or business characteristics.

We find that electricity reliability does not lead to sizable increases in key socioeconomic outcomes for households or business. Further, we analyze alternative reasons for why these impacts do not show up in our analysis, and posit that administrative data on outages may not be sufficient for future research on this topic–as we observe significant differences between ECG-reported outages and self-reported outages of our respondents.

We contribute to the literature studying the economic costs of power outages. Allco1 et al.(2016) and Fisher-Vanden et al.(2015) study firm responses to scheduled rolling blackouts in India and China, respectively, and find that the negative effect of outages on firm productivity is mitigated to some extent by a firm's ability to store inputs over time and re-allocate production to non-outage hours. However, those papers focus on short-run outcomes and are not able to address the possibility that, for example, persistent outages discourage new firms from entering a market in the first place. In addition, neither paper provides evidence on the effect of more frequent and longer duration outages, nor do they study unannounced electricity outages caused by infrastructure failures, which could have a higher impact than the effect they identified due to firms' inability to prepare for unannounced outages by storing inputs or shrinking working hours.

Several papers study the effects of the Dumsor crisis on socioeconomic outcomes in Ghana in particular. Hardy et al.(2019) find that one additional blackout day among small firms is associated with an 11% decrease in weekly profits, and Abeberese et al.(2021) find that one extra day of outages is associated with a 1% reduction in labor productivity and total factor productivity (TFP), however their analyses relied on the assumption that power outages were distributed randomly across firms and households. This is unlikely in this se1ing given anecdotal evidence that blackouts are often concentrated in areas with limited political or economic influence. We are not aware of any additional rigorous quantitative evidence on the effect of the Dumsor crisis on socioeconomic outcomes in Ghana.

2 Background & Context

As is the case for most modern electricity networks, power in Ghana is generated at large power plants. Much of Ghana's electricity is generated through hydroelectric power from the Akosombo Dam, though Ghana also generates electricity from several thermal plants and receives natural gas from Nigeria through the West African Gas Pipeline (WAGP). All generated power is transferred by GRIDco via high-voltage (HV) cables to secondary substations, which transform the power from HV lines to medium-voltage (MV) lines. These MV lines, referred to as 'feeders', connect to a series of additional transformers which convert power to the low-voltage (LV) net- work that serve final grid-connected service drops for individual households and businesses. The Electricity Company of Ghana (ECG) is the primary electricity distributor in Ghana and manages all MV and LV lines for 13 of Ghana's 16 regions.[2]

Starting in late 2012, Ghana began experiencing significant power shortages due to a combination of growing demand, low rainfall, and interrupted WAGP gas supply (Dzansi et al.(2018)). These shortages persisted for the next several years, and forced ECG it to implement rolling blackouts across the country in order to balance the national grid. The period of frequent rolling blackouts from 2013-2016 is referred to as the Dumsor crisis, which translates to "lights on-off" crisis in the local Akan language. These premeditated rolling blackouts are referred to as *load-shedding*, as the reason for the outages relates to an inability of supply to meet the load of electricity demand across the network. Load shedding outages typically lasted 12 hours. The schedule of load shedding was planned at central ECG offices in each region, referred to as Sub-Transmission offices. Schedules for load shedding were generally disseminated at least a few days in advance.

In Accra, these blackouts were implemented at the medium-voltage or feeder level. If a feeder was scheduled for a rolling blackout, all LV infrastructure on that feeder, and all customers connected to that portion of the LV network would experience a power outage simultaneously.[3] Some key pieces of infrastructure were deemed too important to experience rolling blackouts: these included hospitals, police stations, important government buildings, airports, military installments and other important business districts. ECG designated the feeders servicing these areas as exempt from load shedding, to prevent these establishments from experiencing significant power outages. We note, however, that this designation was not entirely black-and-white nor did it necessarily coincide with actual outage data collected from ECG directly during the Dumsor period.

[2]NEDCO is the distributor for the three northern regions of Ghana.

[3]We note that additional infrastructure–which ECG calls "isolators–may exist to restrict power at the sub-feeder level. We provide more discussion of this possibility in Section9

We instead identify which feeders experienced relatively be1er power quality during the Dumsor crisis using data on the universe of feeder-level outages data recorded in ECG situational outage report data, which we outline in detail while discussing our research design in Section5.

Importantly, since EGC implemented load-shedding at the feeder level, if a specific feeder was exempt (*i.e.* received fewer outages), then all customers served by that feeder would receive significantly be1er power, even if they were not the customers EGC wanted to prioritize directly. Our identification strategy leverages exogenous spatial discontinuities in which feeder a household or firm was connected to. As an example, two homes located across the street from each other might be statistically identical in terms of socioeconomic characteristics, but experience significantly different power quality if one happens to be connected to a feeder that also serves a hospital several miles away. We discuss our identification strategy in more detail in the Research design in Section5.

3 Data

We employ a number of data sources to conduct this research, including primary survey data, secondary survey data and a large suite of electricity-related data–including network geodata, outage microdata and other administrative data.

3.1 Electricity Network and Reliability Data

Geospatial data on the electricity network in Accra come from SMEC, a contractor working with ECG to conduct electricity infrastructure improvements. The geospatial data include the locations of LV and MV lines as well as transformers. Most of the LV lines and transformers include information on the feeder (MV) line to which they are connected. In addition to these spatial grid data, we obtained detailed maps of the electricity grid for each electricity district in Accra from SMEC and line schematics for the network of feeders and transformers for each electricity substation in Accra from ECG. We used these maps and line schematics to fill in a large amount of missing information in the geospatial data on the feeders to which particular LV segments and transformers are connected. Taken together, these data allow us to map out the network for each individual feeder across Accra. We do note, however, that the SMEC data and ECG data do not coincide perfectly, and thus, a small portion of the network remains unclassified. We discuss how we work around this unclassified portion of the network in Section5.

We obtain data on outages by feeder for the period 2013-2019 directly from ECG. This incredibly detailed and novel data set contains ECG records of outage events in documents called *situational reports*. Situational reports do not include localized outages below the feeder level, such as if a specific transformer fails or a particular low-voltage line is damaged. However, feeder-level outage data are sufficient for our identification purposes as the main source of variation in electricity reliability we exploit is differences in load shedding during the Dumsor crisis period, which was conducted at the feeder level. While other outages (*e.g.* maintenance, upgrades, emergencies and unplanned outages, etc.) occurred during this period, planned load shedding represents the overwhelming share of outage hours during the Dumsor period.

For each feeder-level outage, the situational reports record the feeder name, outage start and end date and time, and the reason for the outage, such as ECG emergencies, system faults, load shedding, or other non-load shedding planned outages (i.e., for construction, repairs or retrofits). We compile these individual reports to calculate the total outage hours by month for each feeder.

The situational report outage data are central to our priority feeder identification strategy, as we rely on the distribution of monthly load shedding hours in 2015–the peak of the Dumsor crisis period–across feeders to identify which feeders were prioritized for reduced load shedding. We provide more detail on the classification of feeders in the Research Design discussion in Section 5.

3.2 Socioeconomic Data

The Ghana Statistical Service (GSS) divides all of Ghana into Enumeration Areas (EAs), each of which is intended to have roughly the same number of households. The Accra Metropolitan Area includes 1930 EAs. We use geospatial data for the electricity network in Accra and historical outage data provided by the Electricity Company of Ghana (ECG) to select 163 of these EAs located around the boundaries of areas served by "priority" electricity feeders. The Research Design section discusses the method for selecting EAs in more detail. We collect administrative data on these areas from the GSS and complement this with on-the-ground surveys with businesses and households located within these EAs.

3.2.1 Secondary Survey Data

The Ghana Statistical Service (GSS) conducted several business and household surveys in Accra which we use primarily to check whether our sample is representative of the larger population in Accra. We use data from the 2010 Ghana Household Census, the 2015 Labor Force Survey (LFS), the 2017 Ghana Living Standards Survey 7 (GLSS7), and the 2015 Integrated Business Establishment Survey II (IBES II). We obtained these data directly from the GSS.

The census, LFS, and GLSS7 surveys all include as geographic identifiers the EA for each observations. The census covers all EAs in Ghana. We use data from the 2010 census to conduct balance tests for household characteristics across the EAs in our primary survey sample. As the Dumsor crisis period did not begin until 2013, the prioritization of different feeders should not yet have affected any outcomes so households should be statistically similar regardless of the type of feeder serving customers in their EA.

Both the 2017 GLSS7 and 2015 LFS only conducted surveys for a random subset of EAs in Ghana, and there is limited overlap with the sample of EAs selected for our analysis. But, as the samples for both surveys are intended to be representative of urban households in Accra Metropolitan Area, we use data from these surveys to compare against characteristics of households in our sample areas to assess if our sample is representative of Accra at large.

The 2015 IBES II is a survey of a random sample of firms drawing on the 2013 IBES I census of firms in Ghana, and includes a representative sample of firms in the Accra Metropolitan Area. Unfortunately, the IBES data do not include any geographic identifiers, so we cannot match firms to our primary survey sample areas. However, we use information from the IBES II to compare against characteristics of businesses in our sample to again assess the if the businesses in our data are a good statistical representation of the firms in Greater Accra.

3.2.2 Primary Survey Data

Between March and June 2021, we surveyed 1,508 households and 1,505 firms located across 163 EAs that we selected around the boundaries of areas served by priority feeders during the Dumsor crisis.

Our baseline survey targeted an average of 20 respondents (half households and half business) in each selected EA. We selected households based on a random walk strategy. For the random walk, we have enumerators start at the site centroid and assign them a random direction to begin walking, along this route they approach every fourth household or business they encounter along their path until they have reached the target sample size for households and businesses for the site.[4] Researchers commonly use this method in development economics and have validated that it is highly likely to generate a representative sample of the population. Each random walk specifically targets either households or businesses separately. Budget and timing constraints prevented us from pursuing a listing or census of both households and businesses and the random sampling of respondents from those listings, but a well-implemented random walk ensures, at least in expectation, that the respondents in each site is as good as random and representative of the area at large. For businesses, we restricted the set of eligible business respondents to those with fewer than 30 employees, as we aimed our study at small and medium enterprise and not larger and more established firms.

Our survey contains two major components: a contemporaneous component measuring socioeconomic characteristics and outcomes at the time of the survey, and a retrospective component measuring characteristics and outcomes at the time of the Dumsor crisis.

4 Summary Statistics

We report summary statistics for our survey data in Tables 1 for our household sample and Table 2 for our business sample. In each of these tables, we report the mean, median and standard deviation, as well as the minimum, maximum, and interquartile range for each varible. In the final column of each of these tables, we report the Accra-wide mean for a subset of variables that have comparable counterparts in the surveys we mention in the secondary survey data sources we mentioned in Section 3.2.1.

We summarize our survey data for households in Table 1. We find that our respondents are on average 40 years old and nearly 65% of respondents are female. Most (93%) of the respondents have completed primary education, about half have completed secondary education and about 15% have completed post-secondary coursework. Household income is roughly 1500 GHS/month, however, there exists significant variation in this variable across our respondents with an interquartile range between 500 and 2100 GHS/month, with a max of 9050 GHS/month. On average households contain 2.38 adults and 1.39 children – and about 70% of the adults in each household

[4] In small EAs, enumerators approach every third household or business.

held a paid job in the last seven days. On average, households have lived in the same location for 12.79 years, with 58% of the sample moving into their location before the height of the Dumsor crisis in 2015 and 50% moving in prior to the onset of Dumsor in 2012. Households spend around 100 GHS on electricity in a three month period and 93% of the sample have a pre-paid meter. One-in-five households pay someone else for their electricity (*e.g.*, a landlord) as opposed to paying for their electricity directly to ECG. Households experienced around 20 hours of outage in the past 30 days, with an average duration of about 5 hours. Low voltage hours, another measure of poor power quality, happen for about 15 minutes per day, on average. Households own roughly 1600 GHS of appliances on average, which is similar to the average monthly household income. Voltage stabilizers, generators, alternative energy sources (other than the grid) are rare in this sample. Household also do not spend a sizable amount on protective investments and the distribution of spending is heavily skewed with very few households conducting any investment at all (i.e. the 75th percentile spending is 0).

Our household survey respondents appear similar to households in Greater Accra (at least in means) when we compare our outcomes to the census-style data from the GSS. Comparing our mean to the Accra Means in the final column, we conclude that our respondents are similar in terms of household size and number of children, the amount spent on electricity, the number of fridges, TVs and mobile phones and generator ownership. We do note that our households appear have less monthly income than the average household in Greater Accra. However, we are not troubled by this result since we purposefully did not survey households in the richer areas of Greater Accra for a number of reasons that we discuss in Section5.

In Table2, we summarize our survey data for the business sample. We find that business owners are about 39 years old on average, and nearly 65% of respondents are female. Education attainment is similar to our household sample–95% completed primary education, 46% completed secondary education and 11% completed post-secondary education. The firms we survey are predominately single person firms but about 25% of the sample have at least one or more employee. The average last month's revenue and profit are 2582 GHS and 631 GHS, respectively, but these distributions are widely dispersed across respondents with a spread of 0 GHS to 30000 GHS for revenue and -9000 GHS to 5000 GHS for profit. A small share (15%) of firms are co-located with their household dwelling. The average business has been at their location for about 6.5 years– 36% remained in the same place since before the height of the Dumsor crisis in 2015 and 25% remained in the same place since before the onset of Dumsor in 2012. Similar to households, businesses spend about 100 GHS on electricity over three months. Similar to the household sample, 94% are on pre-paid meters and about 15% pay someone other than ECG directly for their electricity. They share similar distributions for outages with the household sample–with about 20 hours of outage over the last 30 days, each lasting on average 4 hours, and roughly 15 minutes of low voltage hours per day. Businesses hold about 1600 GHS of appliances on average. As with the household sample, multiple phase use, generator ownership, alternative energy usage and stabilizer ownership is basically non-existent. The value of protective investments is also quite low and–again–is concentrated among a small number of respondents as the 75th percentile of this variable is 0 GHS.

We find a number of differences between our data and the data for medium-sized Accra businesses in the GSS 2015 Integrated Business Establishment Survey II (IBES II). The firms in the IBES II have

Table 1: Summary Statistics – Household Sample

	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	Accra Mean
Demographics & Education									
Age (years)	1508	40.62	11.01	25.0	31.0	39.0	49.0	65.0	-
Respondent is male	1508	0.35	0.48	0.0	0.0	0.0	1.0	1.0	-
Completed primary education	1508	0.93	0.26	0.0	1.0	1.0	1.0	1.0	-
Completed secondary education	1508	0.46	0.50	0.0	0.0	0.0	1.0	1.0	-
Completed post-secondary education	1508	0.16	0.37	0.0	0.0	0.0	0.0	1.0	-
Household Variables									-
Total HH Income (GHS/Month)	1477	1567.91	1617.16	0.0	500.0	1100.0	2100.0	9050.0	5252.2[a]
Share of Adults with Paid Jobs (Last 7 Days)	1508	0.70	0.37	0.0	0.5	1.0	1.0	1.0	-
Adult members	1508	2.38	1.34	1.0	2.0	2.0	3.0	15.0	2.11[a]
Child (<18) members	1508	1.39	1.43	0.0	0.0	1.0	2.0	8.0	1.34[a]
Location Variables									-
Number of years at location	1476	12.79	10.70	0.0	3.0	9.0	21.0	31.0	-
Moved into location before 2015	1476	0.58	0.49	0.0	0.0	1.0	1.0	1.0	-
Moved into location before 2012	1476	0.50	0.50	0.0	0.0	0.0	1.0	1.0	-
Electricity Variables									-
Electricity Spend (3 Months - GHS)	1496	96.23	86.60	0.0	40.0	74.0	120.0	600.0	88.67[a]
Electricity from prepaid meter	1508	0.93	0.26	0.0	1.0	1.0	1.0	1.0	-
Pays someone else for electricity	1508	0.21	0.41	0.0	0.0	0.0	0.0	1.0	-
Total outage duration (hrs–past 30 days)	1484	20.64	20.34	0.0	5.0	15.0	30.0	96.0	-
Average outage duration (hrs–past 30 days)	1508	4.48	4.01	0.0	1.0	3.0	6.0	18.0	-
Average low voltage hrs/day (past 30 days)	1505	0.26	0.43	0.0	0.0	0.1	0.3	2.4	-
Value of Appliances (GHS)	1508	1665.02	1465.29	0.0	655.0	1380.0	2200.0	20190.0	-
TV Count	1508	1.03	0.55	0.0	1.0	1.0	1.0	8.0	0.85[b]
Fridge/Freezer Count	1508	0.88	0.63	0.0	1.0	1.0	1.0	4.0	0.65[b]
Mobile Phone Count	1508	2.41	1.45	0.0	1.0	2.0	3.0	15.0	3.02[b]
Count of stabilizers	1508	0.16	0.39	0.0	0.0	0.0	0.0	3.0	
Value of Protective Investments	1508	23.20	72.63	0.0	0.0	0.0	0.0	760.0	-
Ever used multiple phases at location	1218	0.03	0.17	0.0	0.0	0.0	0.0	1.0	-
Has generator	1508	0.02	0.13	0.0	0.0	0.0	0.0	1.0	0.02[a]
Alternate Energy (0/1)	1508	0.02	0.15	0.0	0.0	0.0	0.0	1.0	-

[a] : Ghana Statistical Service's 2017 Ghana Living Standards Survey (GLSS)
[b] : 2015 Labor Force Survey (LFS)

Notes:
The number of observations for each variable may differ due to missing values. The survey team records missing values when the respondent refused to answer or answers "I don't know" to a particular question. We only collect values of appliances for TVs and fridges. Values of protective investments include amount spent on fridge/TV guards, "other" surge protectors (excluding stabilizers), and multi-phase systems. Secondary data sources represent the mean from the respective survey for urban households in the Greater Accra Region. Both of these surveys are designed to be representative at the region level and by urban/rural location. We use survey weights to generate representative estimates.

more employees and much more revenue, profit and electricity spending. However, once again, we are not entirely troubled by these discrepancies as they are likely driven differences in our sampling strategy. Our survey excludes business-focused areas, and more importantly, we include only businesses located in non-commercially dominated EAs. In contrast, the IBES II covers only non-household based establishments, which are more likely to occur in the highly commercial areas we do not consider for our study. Thus, we are careful to note that our results only apply to these specific small/medium businesses and/or micro-enterprises and may not generalize to other businesses located in predominately commercial areas.

Table 2: Summary Statistics – Business Sample

	N	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	Accra Mean
Demographics & Education									
Age (years)	1505	38.86	9.81	25.0	31.0	38.0	45.0	65.0	-
Respondent is male	1505	0.34	0.47	0.0	0.0	0.0	1.0	1.0	-
Completed primary education	1505	0.95	0.21	0.0	1.0	1.0	1.0	1.0	-
Completed secondary education	1505	0.46	0.50	0.0	0.0	0.0	1.0	1.0	-
Completed post-secondary education	1505	0.11	0.32	0.0	0.0	0.0	0.0	1.0	-
Business Variables									
Total Employees	1505	2.00	1.87	0.0	1.0	1.0	2.0	22.0	10.31[c]
Total Revenue (Last Month - GHS)	1414	2582.53	4085.91	0.0	700.0	1500.0	3000.0	30000.0	168004[c]
Total Profit (Last Month - GHS)	1368	631.29	867.86	−9000.0	200.0	400.0	800.0	5000.0	111369[c]
Location Variables									
HH/Firm Co-located (=1)	1505	0.15	0.36	0.0	0.0	0.0	0.0	1.0	
Number of years at location	1496	6.51	6.81	0.0	2.0	4.0	9.5	31.0	-
Moved into location before 2015	1496	0.36	0.48	0.0	0.0	0.0	1.0	1.0	-
Moved into location before 2012	1496	0.25	0.43	0.0	0.0	0.0	0.5	1.0	-
Electricity Variables									
Electricity Spend (3 Months - GHS)	1492	107.90	104.23	0.0	50.0	80.0	120.0	600.0	501.68[c]
Electricity from prepaid meter	1505	0.94	0.24	0.0	1.0	1.0	1.0	1.0	-
Pays someone else for electricity	1505	0.15	0.36	0.0	0.0	0.0	0.0	1.0	-
Total outage duration (hrs–past 30 days)	1466	19.72	20.57	0.0	5.0	12.0	27.0	96.0	-
Average outage duration (hrs–past 30 days)	1505	4.32	3.96	0.0	1.0	3.0	6.0	18.0	-
Average low voltage hrs/day (past 30 days)	1503	0.22	0.41	0.0	0.0	0.0	0.3	2.4	-
Value of Appliances (GHS)	1505	1134.04	1714.55	0.0	0.0	650.0	1520.0	26230.0	-
TV Count	1505	0.65	0.95	0.0	0.0	1.0	1.0	20.0	-
Fridge/Freezer Count	1505	0.66	1.02	0.0	0.0	0.0	1.0	20.0	-
Mobile Count	1505	2.12	1.74	0.0	1.0	2.0	2.0	20.0	-
Count of stabilizers	1505	0.13	0.39	0.0	0.0	0.0	0.0	4.0	-
Value of Protective Investments	1505	16.47	84.48	0.0	0.0	0.0	0.0	2000.0	-
Ever used multiple phases at location	1505	0.02	0.15	0.0	0.0	0.0	0.0	1.0	-
Has generator	1505	0.06	0.24	0.0	0.0	0.0	0.0	1.0	-
Alternate Energy (0/1)	1505	0.07	0.25	0.0	0.0	0.0	0.0	1.0	-

[c] : 2015 Integrated Business Establishment Survey II (IBES-II); Ghana Statistical Service.

Notes:
The number of observations for each variable may differ due to missing values. The survey team records missing values when the respondent refused to answer or answers "I don't know" to a particular question. We only collect values of appliances for TVs and fridges. Values of protective investments include amount spent on fridge/TV guards, "other" surge protectors (excluding stabilizers), and multi-phase systems. Summary statistics from the 2015 IBES II represent the mean for businesses in urban Accra with 30 or fewer employees. Businesses in this survey are sampled randomly from the 2013 census of businesses and are intended to be representative of all businesses in Accra.

Of particular importance to our study is understanding how respondents interact with electricity. A key indicator of this is the types of appliances they own. In Figures1 and 2, we display bar- and-whisker plots for the most commonly held appliances in our survey sample. In these figures, the box represents the interquartile range, the vertical line inside the box represent the median, and whiskers–the horizontal lines protruding from each box–represent the 5th-to-95th percentile spread. The red dots represent outlying values. If the vertical line is absent inside a box, it is because the median is coincident with either the 25th or 75th percentile. If there is no box nor line, then the 25th, 50th and 75th percentile are equal. We choose to display a number of appliances that do not have a lot of variation in ownership on purpose – for the variables without a box or whiskers represent appliances where the 5th-to-95th percentile range of ownership is zero.

For households, the most commonly held appliances are radios, mobile phones, ke1les, receivers, blenders and fans. Many households also hold TVs and fridges, but we note that there the absence of a box in these rows indicates that most households only own one of these items. A similar argument applies for stereos, irons, computers and air conditioners. Very few households own electric shavers, sewing machines, blow-driers and straighteners.

Compared to households, businesses hold a larger variety of appliances and the distribution of how many of each appliance they hold is more skewed based on the outlying values. The most commonly held appliance is mobile phones. However, for many of these appliances the median holdings are zero. We interpret these results as refiecting the varieties of productive capital required to run different types of businesses in our sample.

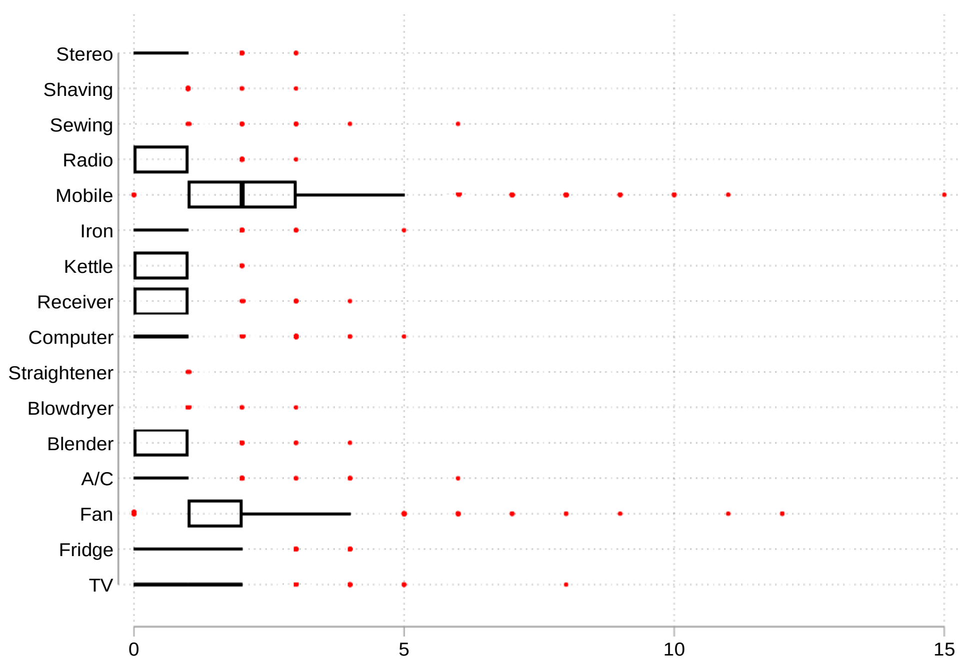


Figure 1: Appliance Counts for Household Respondents

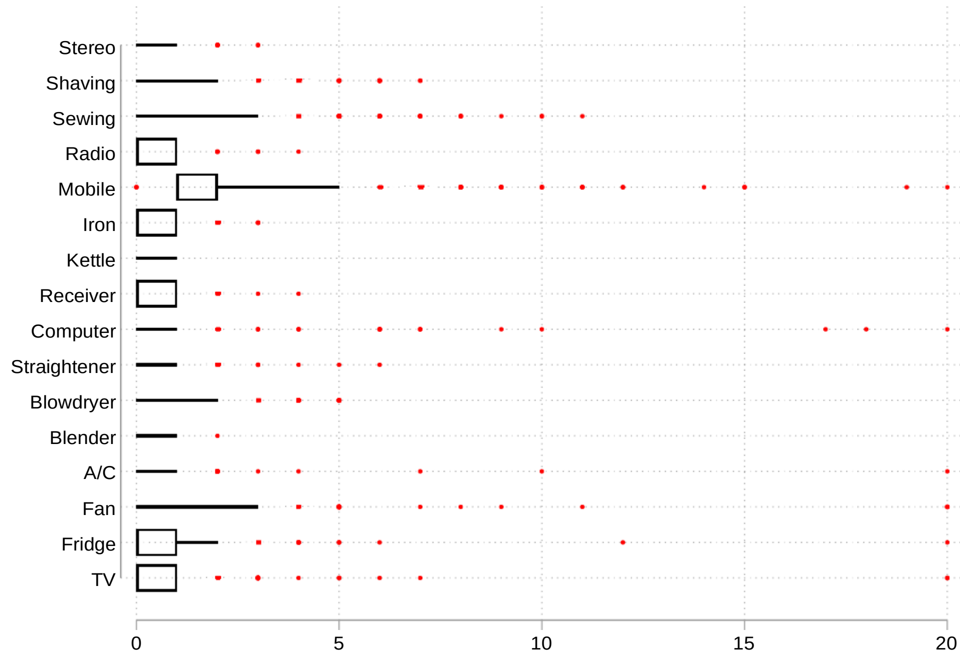


Figure 2: Appliance Counts for Business Respondents

5 Research Design

We exploit spatial discontinuities in the assignment of households and businesses to whether they are connected to a priority feeder or an ordinary feeder to recover causal estimates of the impact of power quality on socioeconomic outcomes. We leverage the fact that priority and ordinary feeders experienced very different levels of load shedding outages during the Dumsor electricity crisis and that these differences are as good-as-random given the pre-determined arrangement of grid infrastructure. We outline our research design and sampling methodology in detail in the following paragraphs.

We begin by identifying spatial areas served by priority and ordinary feeders. We use data from ECG situational reports, which track all outages at the feeder level along with their date, duration, and cause, to identify the feeders that ECG appears to prioritized for low load-shedding during the Dumsor crisis. This period lasted roughly from 2012-2016 with the highest levels of load shedding occurring in 2015, and was characterized by frequent rolling power outages due to power supply issues and typically lasting 12 hours at a time.

We label feeders as “priority” if they experienced fewer than 20 hours per month of load shedding outages on average in 2015, the peak of the Dumsor crisis. Out of 197 feeders in Accra identified in the situational report data, 54 meet this criteria, including 27 that recorded no load shedding outages in 2015. There is a jump in the distribution of monthly outage hours around this threshold, with only a few feeders changing designation if using a threshold as high as 60 hours/month instead of 20 hours/month. Feeders above the threshold of 20 hours/month—which we label as “ordinary”–experienced an average of 182 hours of load shedding hours a month, equivalent to one 12 hour outage every other day for all of 2015. Figure 3 shows the distribution of mean feeder monthly outage hours across 2015.

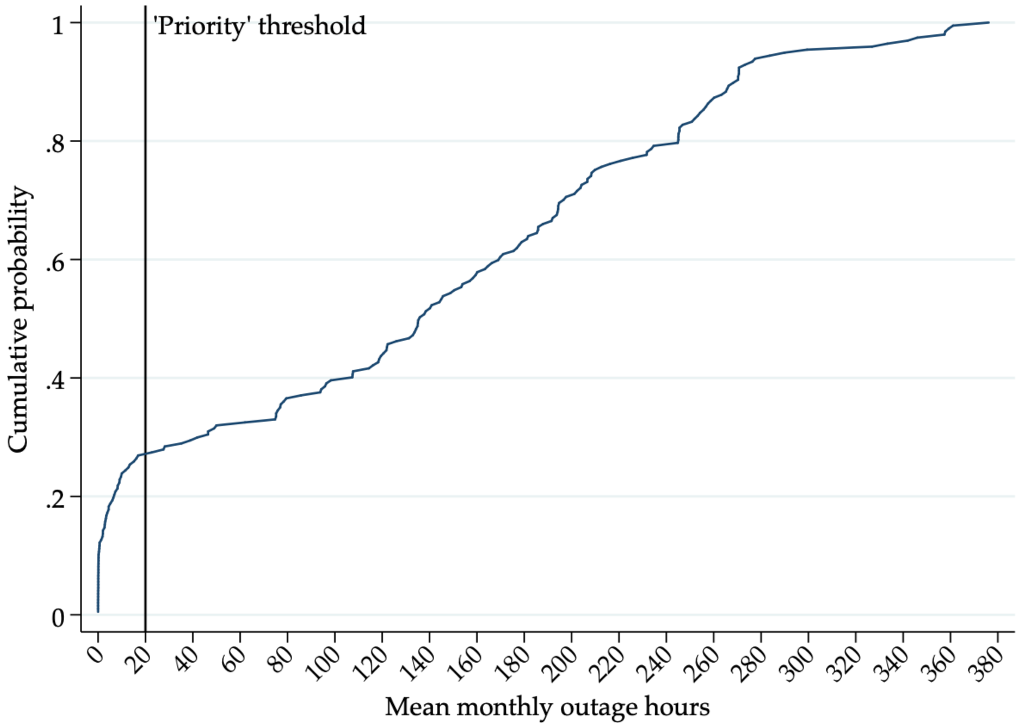


Figure 3: Distribution of Feeder-level Mean Monthly Outage Hours in 2015

Figure 4 illustrates the difference in electricity reliability across the Dumsor crisis period for priority and ordinary feeders in Accra. By construction, the set of priority feeders experience very low average monthly outage hours across the entirety of 2013-2015. This is in stark contrast to the ordinary feeders, which experienced small spikes in outages in early 2013 and 2014, and massive increases in outage hours during the 2015 peak of the Dumsor crisis. During the peak of Dumsor, ordinary feeders reached nearly 300 outage hours per month–or nearly 10 hours per day–in July 2015. These large differences in outage hours represent major differences in electricity reliability experienced by customers on different parts of the electricity network.

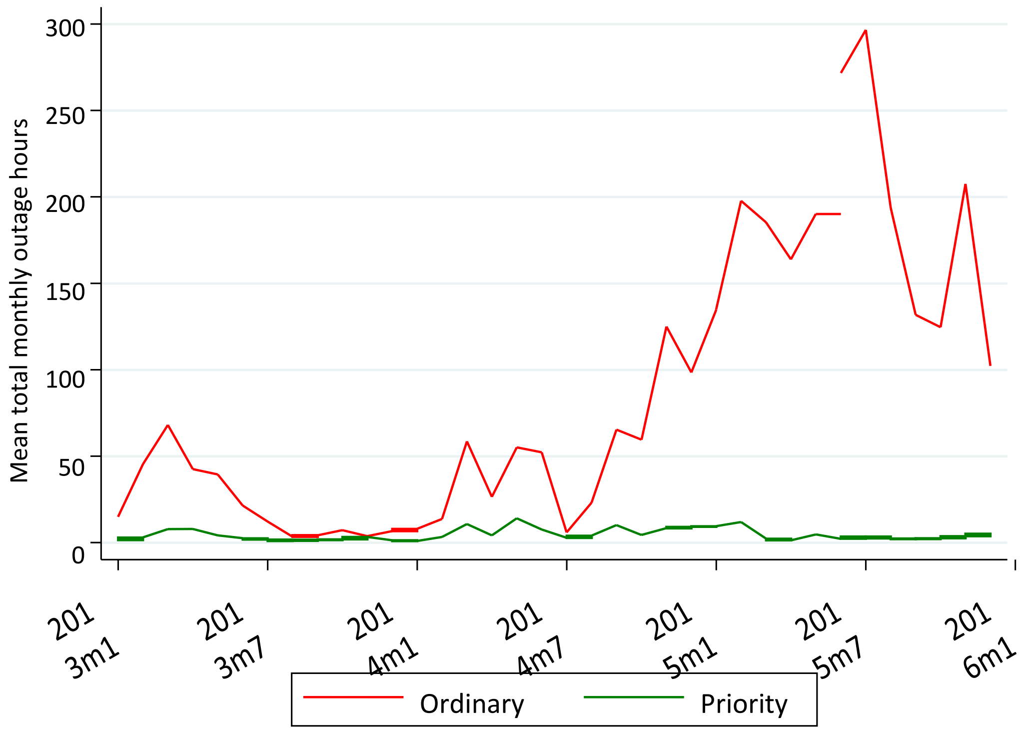


Figure 4: Distribution of Feeder-level Mean Monthly Outage Hours in 2015 by Priority Status

We overlaid the electricity grid map with the set of enumeration areas (EAs) defined by the Ghana Statistical Service (GSS) to identify survey areas that possess good variation for measuring the impacts of electricity reliability. Using spatial data for the electricity network in Accra, we classify and select EAs for inclusion in our sample based on their intersections with priority and ordinary feeders and their associated LV lines. We use EAs as survey sites for two reasons. First, by using EAs as our sampling unit, we are able to use GSS data from the pre-Dumsor period to conduct baseline balance tests (i.e. statistical tests of whether treatment and control sites were statistically similar prior to the Dumsor period across EAs). This is important since we do not have any baseline primary survey data from before the Dumsor period. The second reason is purely logistical–EAs are well-recognized administrative boundaries, which made it feasible for our survey implementation partners at the University of Ghana to conduct household and firm sampling within EA boundaries in Accra, as opposed to more nebulous regions shaped by electricity infrastructure.

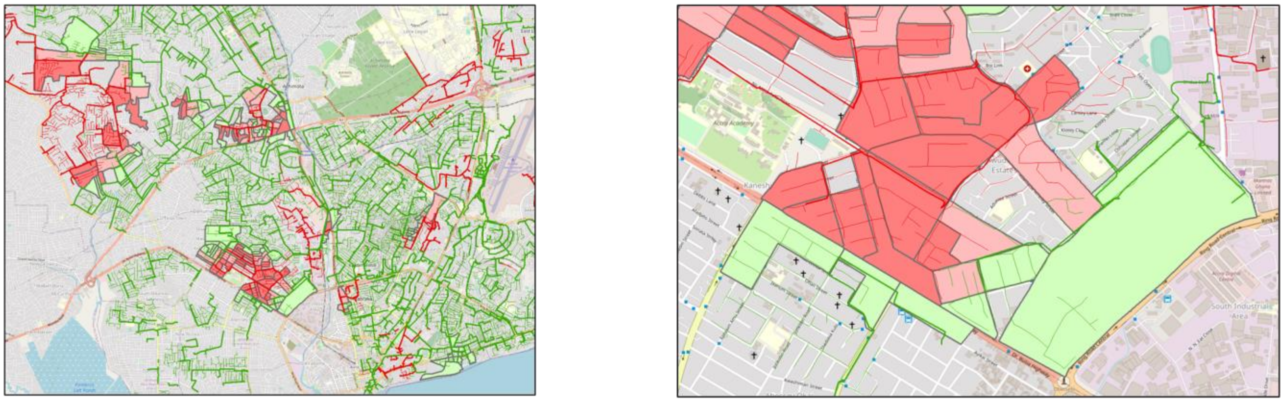
For each EA in Accra, we determine the mix of feeder types that serve customers in that area, and categorize the EA as “priority only,” “ordinary only,” or “mixed” depending on which feeder and LV lines intersect each EAs boundary. Aker identifying the set of EAs traversed by at least one priority feeder or associated LV line–meaning at least some of the households and businesses should be served by that priority feeder–we then identified the set of adjacent “ordinary only” EAs.

Our identification strategy relies on comparing households and businesses that would have experienced similar outcomes over time if not for differences in electricity reliability induced by the feeder from which their electricity supply originates. With this in mind, we focus our site selection on boundary areas around the priority feeder network, as neighboring households and businesses on opposite sites of the priority feeder area boundary should be statistically equivalent in terms of observed characteristics. We therefore drop EAs that do not border another EA of the opposite type. We also rule out boundary areas where satellite imagery suggests the areas served by the different feeder types are different, such as a business district neighboring a residential area where one has a priority feeder and the other has an ordinary feeder. We focused on boundary areas where there is no obvious discontinuity from satellite imagery in the residential or business density across the areas served by different feeder types, so that the only difference is which feeder individuals are connected to. In addition, we excluded sites that could create challenges for surveying, in particular, excluding higher-income neighborhoods characterized by gated compounds.

The final set of sample EAs includes 123 ordinary EAs, and 40 priority EAs, which are organized in 26 clusters of different types of EAs that are adjacent to each other, which we refer to as ”EA Groups”. These sites are served by 44 different electricity feeders, of which 10 we classify as priority.

Panel A in Figure 5 shows the selected EAs classified as either priority, mixed, or ordinary based on the feeders and LV lines that serve these areas. The thick lines represent feeders, while the thin lines represent LV lines. The red lines identify priority feeders or LV lines, whereas the green lines indicate ordinary feeders or LV lines. Additionally, we shade EAs that are only served by priority feeders in red and EAs that are only served by ordinary feeders in green. We color EAs served by both types of feeders (mixed EAs) in pink.

Figure 5: Enumeration Areas (EAs) and Electricity Grid Lines by Priority Status



Panel A Panel B

Notes: Green lines are either ordinary feeders or LV lines connected to ordinary feeders - green shaded areas are EAs that contain exclusively or primarily ordinary feeders. Red lines are either priority feeders or LV lines connected to priority feeders - red shaded areas are EAs that contain exclusively or primarily priority feeders. Panel A displays the entire network across Accra. Panel B displays an example of a neighborhood where priority-only EAs border ordinary-only EAs.

Assigning Respondents to Feeders

While our EA categorization identifies which areas are served by different feeder types, it does not always indicate the feeder type for individual respondents within those sites, especially in mixed (pink) EAs as shown in Figure5 (Panel B). Aker surveying respondents in our sample sites and collecting their GPS locations, we map these locations against the grid network to identify which electricity feeder each respondent was most likely connected to and whether that feeder is categorized as priority or ordinary. Figure6 shows an example of our GPS data. In this figure, we represent survey respondents using black dots and the electricity network using lines. As before, thick lines represent feeders and thin lines represent LV lines. The colors indicate the type of line – red lines depict priority lines, green lines represent the ordinary lines and yellow lines indicate uncategorized lines.

Figure 6: Geodata Example – Mapping Respondents and Electricity Infrastructure

Notes: The black dots indicate the location of survey respondent. The lines represent electricity infrastructure. Thick lines represent feeder lines and thin lines represent LV lines. Red lines represent priority lines, green lines represent ordinary lines and yellow lines indicate uncategorized lines.

Given this rich set of geodata, we use two methods to classify respondents as being connected to a priority or ordinary feeder. In both methods, we begin by identifying feeders and their connected LV lines as priority or ordinary, as described above using the situational reports data. We outline these two methods below:

METHOD 1: MATCHING RESPONDENTS TO THE MOST LIKELY FEEDER

Using ArcGIS, we use each respondent's GPS coordinates and our electricity grid geodata to select the 25 closest LV line segments to each respondent. For each of these segments, we determine what feeder they are connected to, and then identify the full set of distinct feeders that service the closest 25 line segments for each respondent. We restrict this selection to LV lines only since the final service drop for each household or business must originate from an LV line. In other words, there is no way any of our respondents are directly connected to feeder lines given that these feeder lines are medium voltage and not suitable for usage by the consumer directly.

In fact, as mentioned in Section3.1, our geodata on the electricity grid come from SMEC and not ECG directly, and as such, there is significant mismatch between the geodata. We recovered a lot of the mismatched data using ECG line diagram schematics to recover the feeder for LV lines as much as possible. However, these data are messy and, the combination of line or feeder names changing over time, data entry errors and the lack of consistent naming procedures, causes a number of LV lines to remain unclassified or unmatched to a feeder.

As show in Table3, the nearest 25 lines for a majority of respondents originate from only one or two feeders. A smaller proportion have nearby lines from three feeders and very few respondents have nearby lines representing 4 or 5 feeders, with 5 being the maximum number of feeders represented by the closest 25 lines.

Table 3: Distribution of the Number of Feeders Represented by Closest 25 LV Lines for Each Respondent

Number of Feeders	Respondent Count	Percent of Sample
1	842	27.95
2	1,588	52.70
3	515	17.09
4	56	1.86
5	12	0.40

For the 842 households whose nearest 25 lines all originate from the same feeder, we assign that household to ordinary or priority based on the status of that feeder. For the 2171 respondents with more than one feeder servicing the 25 closest segments of the electricity network, we identify the most likely feeder a respondent is connected to as the feeder for the closest segment of the electricity network which is not unclassified. This is based on the facts that customers are connected to the grid via LV lines, that an LV line must be close to the customer for them to be connected to it, and that it is not common for LV lines to pass through an area without connecting to customers in that area.

If the 25 nearest lines are all unclassified, we then match this household to the nearest transformer – and assign that household based on the classification of that transformer.

The main objective for determining each respondent's most likely feeder connection is to determine whether they are connected to a priority or ordinary feeder. For 1705 respondents, none of the closest 25 line segments of the electricity grid connect to a priority feeder, while for 379 respondents all of the closest 25 segments connect to a priority feeder. The remaining 936 respondents possess some mixture of ordinary and priority segments, likely reflecting customers closest to the boundary areas of the areas served by priority feeders. While this may seem inconvenient for our analysis, our research design specifically targeted these "boundary" areas, so we believe this is a feature of our research design and is an indication of proper sampling. Regardless, these cases possess at least some uncertainty about the respondent's priority status. In practice, we keep the priority designation of the feeder for the closest segment for these respondents, as it is likely that households are connected to the closest network in the least cost way possible for EGC. This will almost always correspond to have the shortest possible service drop between the network and the respondent's household or business.

As a diagnostic tool, we use the output of our assignment mechanism to construct a measure of priority probability for each respondent based on the 25 segments associated with that respondent. We do this by calculating inverse distance-weighted proportion of lines that are priority for each respondent.[5] We find a mean priority probability of 72.9% among respondents labeled priority as compared to 13.4% for respondents labeled ordinary.

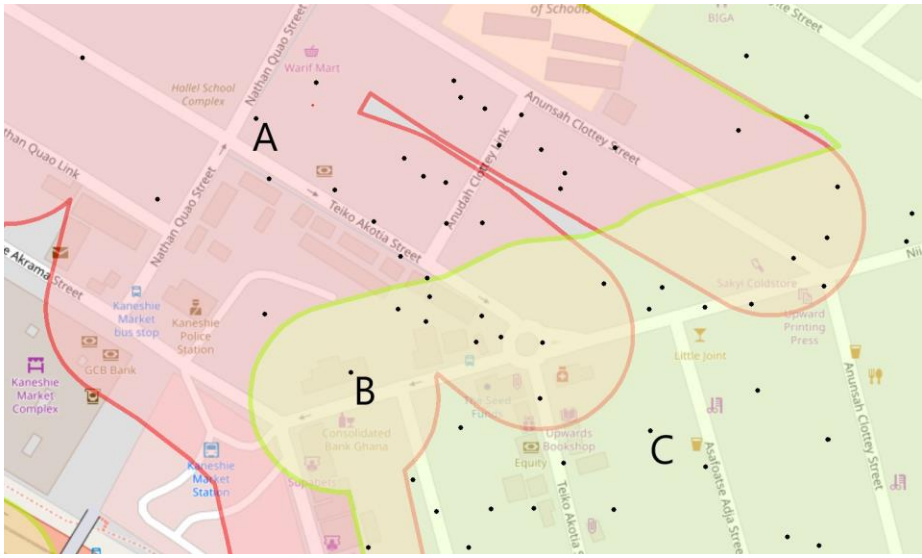
METHOD 2: BUFFER ZONES APPROACH

Our second method takes another geographic approach to assign households to feeder lines. In this case, we use the network data to create areas that are likely to be serviced by each piece of infrastructure, and then match respondents to these areas. In practice, we accomplish this by creating 50-meter perimeters around each LV line, which we will refer to as "buffer zones". If the line associated with a buffer zone is a priority line, then the associated buffer zone is also priority. The same logic applies for ordinary lines and buffer zones. Using these buffer zones and each respondent's GPS coordinates, we then determine the set of buffer zones that intersect each household. If this set consists of entirely priority or ordinary buffer zones, then we classify that respondent as priority or ordinary, respectively. The set of buffer zones for many respondents contains both priority and ordinary zones, and to be conservative, we consider these respondents as connected to an ordinary feeder. Using this procedure 814 respondents are considered on priority feeders while the remaining 2199 are ordinary.

We display an example of how this looks visually in Figure7. The priority buffer zones are shaded in red, whereas the ordinary buffer zones are shaded in yellow. In this figure, the respondent labelled A is classified as priority, since they are located in an area that is only buffered by priority lines. Similarly, the respondent labelled C is classified as ordinary, since they are located in an area only buffered by ordinary lines. Respondent B is located in an area buffered by both priority and ordinary lines, and we make the assertion to classify this household as ordinary.

[5] We do this by first weighting each segment by its inverse distance from the respondent and then dividing the value of the sum of the weight priority line values over the sum of the inverse-distance weighted value for all 25 lines.

Figure 7: Example of a Neighborhood Containing a Border Between Priority and Ordinary Feeders, with GPS locations of surveyed respondents



Notes: Red areas represent priority 50M buffer zones. Yellow areas represent ordinary 50M buffer zones. Each dot is a survey respondent and can be either a business, home, or a respondent whose home and business are co-located. Respondent A is in a priority only buffer-zone area and is classified as priority. Respondent B is in an ordinary only buffer-zone area and is classified as ordinary. Respondent C is in a mixed buffer-zone area, which we classify as ordinary.

6 Empirical Strategy

Given that we are able to use our data to assign households to ordinary or priority feeders, we can use this categorization to estimate the causal impact based on cross-sectional variation using the quasi-experimental assignment of priority status for identification. First, we validate the empirical strategy by testing if customers on priority and non-priority feeders exhibit statistical balance prior to Dumsor. Second, we estimate treatment effects of being exposed to fewer outages during Dumsor. In both cases, we estimate the following regression equation:

$$Y_{ift} = \alpha + \theta PRIORITY_{if} + \bar{\beta} X_{ift} + \varepsilon_{ift} \tag{1}$$

where Y_{ift} measures electricity consumption, appliance ownership, income, profits, or socioeconomic outcomes for firm or household i connected to feeder f in period t. The treatment variable $PRIORITY_{if}$ is a measure of whether the customer is served by a priority feeder. βX_{ift} is a set of controls such as industry (for firms) or household size (for households) that will improve the precision of our estimates. ε_{ift} captures unobserved factors that affect electricity and socioeconomic outcomes for households over time. θ is the parameter of interest because it measures the impact on the outcome variable of receiving priority power reliably during the Dumsor period.

In general, we test the hypothesis that being on a priority feeder during the Dumsor period had a positive impact (defined based on the outcome, for example an increase in household electricity consumption or firm profits or a decrease in spending on electricity protection) on the outcome measure under consideration against the null hypothesis of no impact.

Broadly, outcome data include measures that are contemporary to the time of the survey and measures from a previous period when power outages occurred more frequently (the Dumsor crisis).

In general, we test the hypothesis that being on a priority feeder during the Dumsor period had a positive impact (defined based on the outcome, for example, an increase in household electricity consumption or firm profits or a decrease in spending on electricity protection) on the outcome measure under consideration against the null hypothesis of no impact. We test this using a wide variety of outcome variables. Outcomes considered include electricity consumption, appliance ownership and use, spending on electricity protection and reliability coping mechanisms (including generators), household income and labor participation, and firm operations, costs, revenues, and profits. The hypothesized impact of being on a priority feeder during the Dumsor crisis will vary depending on the outcome being considered–an ”improvement” in the outcome might be either an increase or a decrease in the variable. The key outcomes of interest are economic out- comes variables, such as, household incomes and firm profits. However, we also include various other socioeconomic outcomes which may be expected to have an impact on incomes and profits.

To increase precision of our estimates, control variables may include a variety of household and firm characteristics, any relevant differences in electricity access not captured by the priority feeder dummy variable, and the timing of the survey. Key household control variables include measures of household size and education-level, and key firm control variables include industry. Both specifications include controls for whether that household is also the site of a business. Our identification approach assumes that exogenous variables other than the electricity network should not differ systematically across treatment and control sites. However, we include EA- group level fixed effects to increase the precision of our estimated by controlling for any time- invariant differences across EA groups. Our empirical approach will not be biased as long as all other factors that determine the outcome (e.g. tariffs, income, weather) affect both our treatment and control groups equally.

7 Selection on Observables & Balance Testing

Our identification strategy relies on the only difference between our sample of households and firms being whether they are connected to a priority or an ordinary feeder. If we are to inter- pret our analysis as casual, we must rule out that these results are either driven by pre-existing pre-treatment differences between priority or ordinary groups or that these results are driven by endogenous moving behavior, where people who are more likely to benefit from electricity services move to priority areas as a result of Dumsor.

We conduct balance testing in two ways–first, we use GSS census data from before the Dumsor crisis to test for balance across the EAs in our sample and second, we test for balance using our survey data directly.

However, before we highlight that analysis, we choose to first analyze the other threat to identification–that people who are more likely to benefit from electricity services move as a result of Dumsor to priority areas with be1er electricity services. If this is true, any improvements in socioeconomic outcomes could derive from underlying characteristics of these movers as opposed to an improvement in electricity supply, even if our sample appears balanced at the onset of our study.

Endogenous Moving

Since we are worried about endogenous moving, we use our data to directly test for systematic endogenous moving in our sample. In this case, we estimate a regression with our treatment variables as dependent variables and two independent variables: a measure of how many of your two most-adjacent neighbors are the same as they were in 2015 and an indicator for if this household or business moved into their location prior to 2015. If this household moved since 2015, we assume their two most recent neighbors changed as well, and set the value of this variable to zero for those households that did not answer this question. For this analysis, we control for EA-group level characteristics via fixed effects in these regressions. We do this to control for wider time-invariant geographic variation, which focuses our analysis on within EA-group variation. We also account for any error correlation within EA-group by clustering our standard errors at this level. We run these regressions for the household and business sample separately, and analyze these data for both of our treatment variables.

In Tables4 and 5, we run three regressions for each treatment variable–one with just the variable measuring if households moved in their household before 2015, one with just the variable of whether they have the same adjacent neighbors since June-2015 and a third including both of these variables. Across all specifications for both treatment variables and samples, we show that our treatment indicator is not explained by either of these variables. This analysis supports the conclusion that households and businesses are not moving in response to the priority status of their electricity supply. We interpret this result as suggesting that any subsequent results are not driven by endogenous moving behavior.

Table 4: Endogeneity of Moving – Households

	Priority (Base)			Priority 2 (50M)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moved into location before 2015	−0.006		−0.028	−0.003		−0.003
	(0.026)		(0.047)	(0.023)		(0.044)
Share of Same Adjacent Neighbors since June-15		0.000	0.026		−0.004	−0.002
		(0.030)	(0.054)		(0.027)	(0.052)
Constant	0.324***	0.321***	0.325***	0.264***	0.264***	0.264***
	(0.015)	(0.014)	(0.015)	(0.013)	(0.013)	(0.013)
Observations	1476	1444	1444	1476	1444	1444
Number of Clusters	26	26	26	26	26	26

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Standard errors clustered by EA groups. Share of Same Adjacent Neighbors is based on the two nearest neighbors and takes values of 0, 0.5 or 1. All regressions include controls for if this household is also a place of business and fixed effects for EA groups based on the relevant treatment variable.

Table 5: Endogeneity of Moving – Businesses

	Priority (Base)			Priority 2 (50M)		
	(1)	(2)	(3)	(4)	(5)	(6)
Moved into location before 2015	0.006		−0.037	−0.005		−0.002
	(0.017)		(0.036)	(0.022)		(0.039)
Share of Same Adjacent Neighbors since June-15		0.023	0.058		0.003	0.004
		(0.022)	(0.044)		(0.026)	(0.041)
Constant	0.323***	0.320***	0.323***	0.280***	0.281***	0.281***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)
Observations	1496	1464	1464	1496	1464	1464
Number of Clusters	26	26	26	26	26	26

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Standard errors clustered by EA groups. Share of Same Adjacent Neighbors is based on the two nearest neighbors and takes values of 0, 0.5 or 1. All regressions include controls for if this household is also a place of business and fixed effects for EA groups based on the relevant treatment variable.

Balance Testing

Now that we have determined that endogenous moving is unlikely to impact our results, we next turn to verifying that our results are not driven by pre-existing differences between priority and ordinary areas. We conduct this analysis in two ways: first, we match GSS census data from before the Dumsor crisis for the same EAs used in our analysis to test how the distribution of various characteristics compare across our ordinary and priority classifications prior to Dumsor; second, we use our survey data to test for balance within our sample directly.

For the GSS comparisons, we collect GSS census data for each EA in our sample and assign each EA to priority or ordinary status based on whether the majority of households in our sample within each EA are priority or ordinary. For example, if an EA contains 11 respondents and 7 of them are classified as priority, then that EA is classified as priority. We then assign the GSS census data from that same EA to the priority category shared by that EA, and conduct difference-in-means tests across the two groups of EAs–priority and ordinary. Since each EA has a different number of people, we convert each measure into a proportion for each EA and report the mean and standard deviation of these proportions across EAs. To test for differences in covariates across the two groups, we run a regression for each variable with the characteristic variable as the dependent variable and the priority indicator as the independent variable. We report the coefficient estimate associated with the priority variable and this estimate's p-value. Throughout, we control for EA Groups and weight the observations by the total population of each EA as indicated in the GSS Census data.

We display the results of these balance test in Tables 6 and 7. The first three columns report the mean proportion across all EAs and standard deviation in parentheses for each balance-test variable. The fourth and fifth columns report the coefficient from the population weighted difference- test regression (including the EA-group fixed effects) and the p-value of this difference, respectively.[6]

[6] The inclusion of EA-group fixed effects means that the difference coefficient may not coincide with the simple difference in the means in the other columns. This is by design as the inclusion of EA-group fixed effects will impact

We report the results of our balance testing analysis using our treatment variable defined by the closest feeder in Table6. Using this categorization, we classify 119 EAs as ordinary and 40 as priority. These results show that our sample is roughly 50% female, although ordinary areas have slightly more females and this difference marginally statistically significant with a *p*-value of .094. These results also show that about 80% of the sample is Christian – with no statistically significant difference between priority and ordinary areas. About 90% of people have some formal education, about 35% have a high-school degree and roughly 8% are not-literate. Notably, the difference in high-school education a1ainment looks quite large between ordinary and priority households, but after controlling EA-group fixed effects in our difference regression, this difference is almost zero and is statistically insignificant. We see a similar pattern with modern cooking fuel usage and computer ownership. Employment is balanced across the two groups and so is telephone line ownership and internet facility usage. Importantly, electricity access is ubiquitous with about 93% of households having access to grid-derived mains or a private generator. Importantly, this variable is balanced across priority and ordinary areas. In terms of structure characteristics, households are balanced on terms of non-improved flooring, roof and outer wall construction.

We display the results of our census-level balance tests using the buffer-zone assignment ofpriority status in Table7. Using this treatment variable we 119 EAs as ordinary and 40 EAs as priority. The results from this analysis are quite similar to our analysis using our nearest line assignment mechanisms, which is no surprise given the considerable overlap of these two definitions for most respondents. Notably, we measure no variables that are statistically different in this analysis.

We conclude from this analysis that our sample areas are well-balanced when we consider the EA-wide pre-Dumsor data from the GSS census. We note, however, that even if the areas we sampled from are balanced, this does not guarantee our survey sample is balanced as well, which we turn to next.

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the value of the estimated difference-in-mean coefficient.

Table 6: Balance check between priority and ordinary EAs - closest feeder

Variable	All	Mean Ordinary	Priority	Difference	Diff *p*-value
Female	0.516	0.516	0.515	-0.010	0.094
	(0.028)	(0.029)	(0.027)		
Christians	0.831	0.811	0.876	0.021	0.139
	(0.188)	(0.204)	(0.134)		
Ever A1ended School	0.929	0.924	0.940	-0.003	0.698
	(0.055)	(0.059)	(0.044)		
Minimum HS Degree	0.359	0.344	0.393	-0.001	0.958
	(0.091)	(0.086)	(0.094)		
Modern cooking fuel	0.456	0.444	0.483	0.000	0.996
	(0.174)	(0.174)	(0.172)		
Owns a Computer	0.044	0.041	0.051	0.000	0.997
	(0.026)	(0.023)	(0.031)		
Employee/self-emp. with employees	0.447	0.440	0.463	0.013	0.484
	(0.099)	(0.100)	(0.096)		
Owns a Fixed Telephone Line	0.013	0.010	0.021	0.002	0.477
	(0.018)	(0.010)	(0.028)		
Earth/mud floor	0.053	0.051	0.057	0.007	0.751
	(0.119)	(0.124)	(0.109)		
Uses an internet facility	0.180	0.170	0.202	-0.011	0.619
	(0.110)	(0.105)	(0.118)		
Electricity (mains/private generator)	0.927	0.923	0.937	-0.009	0.462
	(0.070)	(0.077)	(0.051)		
Not literate	0.078	0.084	0.065	0.003	0.703
	(0.065)	(0.069)	(0.050)		
Owns a mobile phone	0.762	0.760	0.765	-0.005	0.373
	(0.033)	(0.031)	(0.036)		
Roof not improved	0.015	0.015	0.016	0.002	0.720
	(0.027)	(0.027)	(0.029)		
Outerwall not improved	0.112	0.121	0.092	0.030	0.332
	(0.140)	(0.153)	(0.105)		
Number of EAs	159	111	48		

Notes: Outcomes are from the GSS 2010 Census at the EA level. Standard deviations in parentheses. There are 48 priority EAs and 111 ordinary EAs (there are no census data for 4 EAs). These 159 EAs are organized in 26 groups. 23 groups have at least one priority EA. The other 3 groups have only ordinary adjacent EAs. Given the lower number of priority EAs, most groups have more ordinary EAs than priority EAs. The coefficient and the p-value are the result of a regression of the indicator variable "Priority" on the variable including group fixed effects and population weights for each EA. This "Priority" variable is based on the closest feeder.

Table 7: Balance check between priority and ordinary EAs - 50m-Buffer Zone

Variable	Mean All	Ordinary	Priority	Difference	Diff. *p*-value
Female	0.516	0.516	0.515	-0.009	0.138
	(0.028)	(0.029)	(0.027)		
Christians	0.831	0.823	0.854	0.011	0.445
	(0.188)	(0.189)	(0.184)		
Ever A1ended School	0.929	0.926	0.937	0.007	0.416
	(0.055)	(0.058)	(0.046)		
Minimum HS Degree	0.359	0.350	0.386	-0.005	0.715
	(0.091)	(0.085)	(0.103)		
Modern cooking fuel	0.456	0.455	0.459	-0.003	0.903
	(0.174)	(0.172)	(0.182)		
Owns a Computer	0.044	0.043	0.046	-0.004	0.421
	(0.026)	(0.024)	(0.032)		
Employee/self-emp. with employees	0.447	0.443	0.460	0.013	0.480
	(0.099)	(0.099)	(0.099)		
Owns a Fixed Telephone Line	0.013	0.011	0.021	0.000	0.996
	(0.018)	(0.011)	(0.030)		
Earth/mud floor	0.053	0.052	0.054	0.006	0.773
	(0.119)	(0.124)	(0.107)		
Uses an internet facility	0.180	0.174	0.196	-0.019	0.394
	(0.110)	(0.108)	(0.115)		
Electricity (mains/private generator)	0.927	0.924	0.937	-0.012	0.345
	(0.070)	(0.075)	(0.053)		
Not literate	0.078	0.081	0.068	-0.008	0.395
	(0.065)	(0.068)	(0.053)		
Owns a mobile phone	0.762	0.761	0.765	-0.007	0.246
	(0.033)	(0.031)	(0.037)		
Roof not improved	0.015	0.015	0.018	0.006	0.403
	(0.027)	(0.026)	(0.032)		
Outerwall not improved	0.112	0.116	0.102	0.014	0.650
	(0.140)	(0.149)	(0.111)		
Number of EAs	159	119	40		

Notes: Outcomes are from the GSS 2010 Census at the EA level. Standard deviations in parentheses. There are 40 priority EAs and 119 ordinary EAs (there are no census data for 4 EAs). These 159 EAs are organized in 26 groups. 21 groups have at least one priority EA. The other 5 groups have only ordinary adjacent EAs. Given the lower number of priority EAs, most groups have more ordinary EAs than priority EAs. The coefficient and the p-value are the result of a regression of the indicator variable "Priority" on the variable including group fixed effects and population weights for each EA. This "Priority" variable is based on the 50-meter buffer zones.

Absent a proper baseline survey, we conduct some additional balance testing using our survey data. Since the survey data comes from after the treatment–we restrict this analysis to the subset of individual who did not move after 2015 and are 25 years of age or older at the time of survey. We refer to this sample as the ”recall eligible” sample. With these restrictions, we can accurately test for balance across ”pre-determined” variables (i.e. variable that are unlikely to be affected by treatment) such as age, gender, education status, etc. Around 55% of respondents are eligible for inclusion in this ”recall” sample across both types of respondents. Since we've ruled out that the priority status treatment might have led to differential rates of moving of households and businesses in priority and ordinary areas, we can use this analysis to test for balance since the respondents that remain in these areas should be representative of the larger population in that area prior to the peak of the Dumsor crisis. As before, we conduct this analysis separately for each of our treatment variables and household and business samples separately.

In Table8we test for balance for our household sample using both of our treatment variables. Using each variable, our household respondents are statistically similar in terms of age, gender, education, and whether they moved to their location before 2015 or 2012. Using our nearest line assignment mechanism, ordinary household respondents moved in their location about a year later on average. However, this same difference is not statistically significant using our buffer-zone assignment variable.

We display this same analysis for the business sample in Table9. In this sample, the business respondents are statistically similar along all dimensions for both treatment variables, with the exception of age using our nearest line assignment mechanism. In this case, we find priority households are about 1.5 years older than their ordinary counterparts.

While these balance tests suggest that these groups are similar on most dimensions we test, we will include age and number of years at location as control variables in our regressions to control for those variables that show differences in their means, as they may interact with our estimated treatment effects.

Table 8: Balance in Mean for Recall Respondents in Household Sample

	Ordinary Mean	N	Priority Mean	N	Difference	*p*-value
PANEL A: NEAREST LINE PRIORITY ASSIGNMENT						
Age (years)	43.20	666	43.39	302	−0.19	0.803
Respondent is male	0.35	666	0.33	302	0.02	0.569
Completed primary education	0.91	666	0.92	302	−0.01	0.689
Completed secondary education	0.41	666	0.44	302	−0.02	0.510
Completed post-secondary education	0.16	666	0.14	302	0.02	0.447
Number of years at location	17.47	666	18.85	302	−1.38	0.046
Moved into location before 2015	0.88	666	0.87	302	0.00	0.846
Moved into location before 2012	0.75	666	0.76	302	−0.02	0.607
PANEL B: 50M BUFFER-ZONE PRIORITY ASSIGNMENT						
Age (years)	43.29	719	43.16	249	0.13	0.871
Respondent is male	0.34	719	0.35	249	−0.01	0.719
Completed primary education	0.91	719	0.93	249	−0.02	0.393
Completed secondary education	0.41	719	0.45	249	−0.04	0.234
Completed post-secondary education	0.15	719	0.15	249	0.00	0.867
Number of years at location	17.65	719	18.63	249	−0.98	0.180
Moved into location before 2015	0.87	719	0.88	249	−0.00	0.932
Moved into location before 2012	0.75	719	0.76	249	−0.01	0.866

Table 9: Balance-in-Mean for Recall Respondents in Business Sample

	Ordinary Mean	N	Priority Mean	N	Difference	*p*-value
PANEL A: NEAREST LINE PRIORITY ASSIGNMENT						
Age (years)	41.85	458	43.39	218	−1.55	0.047
Respondent is male	0.31	458	0.32	218	−0.01	0.730
Completed primary education	0.95	458	0.94	218	0.01	0.541
Completed secondary education	0.39	458	0.42	218	−0.03	0.512
Completed post-secondary education	0.09	458	0.10	218	−0.01	0.708
Number of years at location	11.08	458	11.89	218	−0.81	0.187
Moved into location before 2015	0.75	458	0.80	218	−0.04	0.186
Moved into location before 2012	0.52	458	0.59	218	−0.06	0.122
PANEL B: 50M BUFFER-ZONE PRIORITY ASSIGNMENT						
Age (years)	42.05	491	43.15	185	−1.10	0.186
Respondent is male	0.32	491	0.30	185	0.01	0.745
Completed primary education	0.95	491	0.95	185	−0.00	0.819
Completed secondary education	0.39	491	0.42	185	−0.02	0.587
Completed post-secondary education	0.10	491	0.08	185	0.02	0.396
Number of years at location	11.10	491	11.98	185	−0.89	0.170
Moved into location before 2015	0.75	491	0.81	185	−0.05	0.140
Moved into location before 2012	0.52	491	0.60	185	−0.08	0.073

8 Regression Results

We group our causal results into three categories – power-related variables, household-specific outcomes and business outcomes. Each set of variables is estimated for households and businesses separately–as priority assignment is likely to affect these types of respondents in systematically different ways and we do not want this underlying difference driving any results.

In Tables10-13, we report a series of coefficient estimates, where each estimate comes from a singular regression of the form in Equation1using our two distinct treatment variables as described in Section5. Thus, each reported coefficient represents a different regression. In these tables, column (1) highlights the treatment effects based on our first treatment definition based on the most likely or closest LV line, whereas column (2) reports the control group mean for each respective variable using that same treatment definition. Columns (3) and (4) are defined similarly, just using our buffer zone approach to assign respondents to the priority treatment. Column (5) reports the number of observations in each regression, which may differ across variables based on the non-response of some households to certain questions on our survey.

Household Analysis

In Table10, we report the coefficient estimates for our primary household-specific power outcomes. The majority of these variables show that the impact of being connected to a priority feeder–and the improved electricity supply–does not lead to improvements in a number of dimensions that we hypothesized it would at the onset of this study in our pre-analysis plan–such as WTP for electricity reliability or a generator, the value of protective investments, the value of appliances, the use of alternate energy (currently or during the Dumsor period) or the value of convenience appliances.

In fact, the singular variable in this set that shows signs of significance in our se1ing is the willingness to pay (WTP) for 50 GHS of electricity credit.[7] Respondents were presented with a sequence of hypothetical dichotomous choices, starting with a choice between a 50 GHS electricity transfer and a mobile money transfer of the same amount. The cash amount of each subsequent choice depended on the previous response. WTP is the highest cash transfer amount the respondent rejected in favor of the electricity transfer, up to a maximum of 100 GHS and a minimum of 10 GHS. This approach is commonly used to elicit WTP for goods or services (Alberini and Cooper,2000), including for electricity in different African countries (Abdullah and Jeanty,2011; Deutschmann et al.,2021;Sievert and Steinbuks,2020). Our results indicate that households connected to priority feeders are willing to pay approximately 5 GHS more for a 50 GHS credit than households connected to ordinary feeders, for whom mean WTP is nearly 60 GHS. This suggests that households value electricity credits more than money on average. Berkouwer et al.(2022) use an identical WTP elicitation method with a different sample of electricity customers in Accra and obtain similar results. Their appendix describes the efforts taken to test the validity of the results, which are robust to calling respondents back to elicit WTP again and are consistent within respondents over time and across enumerators.

Berkouwer et al.(2021) explore reasons why Ghanaian respondents might value electricity more than cash, in contrast to Kenyan electricity customers. The same reasons apply in this sample. Ghanaian customers face high transaction costs of purchasing electricity: 93% of sample households are connected to pre-paid electricity meters and nearly all of these must visit an ECG vendor in-person to purchase electricity credit before being able to consume electricity. Low adoption of mobile money makes a mobile money transfer less useful in contrast to an electricity transfer, which all sample households can use. When asked why they prefer electricity to cash, respondents in our sample give two main reasons in addition to the above. Households preferring electricity commonly report they would use the cash for electricity anyway (42.5% of our sample), reflecting that 50 GHS in electricity credit is inframarginal for many households. Finally, 51.6% respondents express a desire to be able commit to spending money on electricity.

Higher willingness to pay for electricity credit in priority areas relative to control areas may also be a byproduct of having a be1er and more stable energy service. For example, if households in priority areas expect a higher level of electricity reliability, they may invest more in electrical devices, which may increase their marginal benefit from more electricity. However, the coefficient estimate on the value of appliances is negative (but not significantly different from zero) and the coefficient on the count of appliances is also indistinguishable from zero.[8]

However, even absent differences in the value or number of appliances, priority households may be more reliant or habitual about the appliances they do have–maybe even based on their previous experience with a be1er electricity supply–so that they still have a higher willingness-to-pay for

[7] WTP was elicited using a contingent valuation method.

[8] Due to a mass of missing data for the value of most appliances, the value of appliances data only measures the value of TVs and refrigerators, which does not capture the full value of all appliances but given these are the most likely owned appliances beside mobile phones, we posit this represents the majority of appliance holdings for most households.

electricity than households who are more often subject to less power availability. However, we note that the coefficients on the number of hours households use lights, TV and cooling appliances is statistically similar across ordinary and priority households. These findings do not entirely rule out this possibility as they only represent a small number of commonly owned appliances, but certainly do not support this hypothesis directly.

Table 10: Household Power Variables – Primary Outcomes

	Priority (Base)		Priority 2 (50M)		Obs.
	(1)	(2)	(3)	(4)	(5)
WTP Perfect Reliability (GHS/Month)	0.842	17.953	−0.318	17.929	1500.000
	(1.169)		(1.189)		
WTP Half of Current Outage (GHS/Month)	0.150	6.334	0.064	6.245	1473.000
	(0.640)		(0.753)		
WTP for Generator (GHS)	216.108	2374.168	285.896	2368.752	1475.000
	(223.749)		(205.944)		
WTP for 50 GHS Electricity Credit	4.909**	59.216	5.146*	59.168	1500.000
	(2.454)		(2.636)		
Value of Protective Investments	2.026	25.347	3.854	24.521	1500.000
	(4.663)		(5.388)		
Value of Protective Investment (June 2015)	0.430	6.657	0.266	6.465	1500.000
	(2.063)		(1.844)		
Amount Paid for Multi-phase System in Dumsor (GHS)	0.430	6.657	0.266	6.465	1500.000
	(2.063)		(1.844)		
Value of Appliances (GHS)	109.331	1638.005	102.821	1636.842	1500.000
	(79.676)		(82.994)		
Count of Appliances	0.021	6.501	0.144	6.459	1500.000
	(0.268)		(0.261)		
Daily TV Use (Hours)	−0.122	4.808	0.142	4.745	1500.000
	(0.255)		(0.211)		
Daily Cooling Appliance Use (Hours)	−0.575	11.450	0.344	11.227	1500.000
	(0.491)		(0.332)		
Daily Lightbulb Use (Hours)	−0.000	7.050	0.149	6.980	1490.000
	(0.259)		(0.261)		
Alternate Energy (0/1)	0.003	0.022	0.010	0.020	1500.000
	(0.008)		(0.009)		
Alternate Energy (Dumsor) (0/1)	0.014	0.065	−0.006	0.067	963.000
	(0.028)		(0.019)		
Value of Convenience Appliances	45.537	786.802	1.831	793.786	1500.000
	(46.486)		(42.848)		
Column Type	Coef.	Ctrl. Mean	Coef.	Ctrl. Mean	
Fixed Effects	cluster_priority_0		cluster_priority_1		
SE Cluster	cluster_priority_0		cluster_priority_1		

We report the results on other socioeconomic household-level outcomes in Table11. Notably, we find some evidence that households in priority areas have higher current household income, but this result is only significant using our priority definition based on the nearest power line. The sign of the effect remains the same using our buffer-zone approach – however the magnitude of this impact shrinks, thus rendering this result insignificant in the buffer-zone specification. Further, we find some evidence that households in priority areas are less likely to burn dirty cooking fuels, but again, this result is not robust across specifications. Across the remaining variables in this table, we find no evidence of differences related to treatment. This includes the number of adults with paid jobs, rent payments, primary education a1ainment for children, household health issues or challenges and a study light quality index.

Table 11: Household Outcome Variables – Primary Outcomes

	Priority (Base)		Priority 2 (50M)		Obs.
	(1)	(2)	(3)	(4)	(5)
Total HH Income (GHS/Month)	247.792**	1512.360	112.508	1546.387	1470.000
	(102.089)		(93.851)		
Share of Adults with Paid Jobs (Last 7 Days)	0.052	0.677	0.048	0.677	1500.000
	(0.036)		(0.037)		
Share of Adults with Paid Jobs (Dumsor)	0.016	0.696	0.031	0.689	963.000
	(0.043)		(0.042)		
Rent Payment (GHS/Month)	17.548	155.565	24.645	155.218	658.000
	(16.737)		(15.001)		
Rent Payment during Dumsor (GHS/Month)	8.609	61.134	11.701	60.644	509.000
	(11.367)		(9.517)		
Share Completed Primary Education (Age 12-18)	0.061	0.880	0.062	0.883	501.000
	(0.039)		(0.038)		
HH Challenge Index	−0.042	−0.016	−0.068	−0.011	1500.000
	(0.070)		(0.070)		
HH Reliability Effect Index	0.097	0.021	0.041	0.020	1500.000
	(0.060)		(0.066)		
HH Reliability Effect Index (Dumsor)	−0.070	0.025	−0.099	0.017	963.000
	(0.086)		(0.094)		
HH Health Issues Index	−0.033	0.047	0.050	0.017	1496.000
	(0.071)		(0.084)		
HH Study Light Quality Index	−0.061	0.011	−0.021	−0.007	1490.000
	(0.069)		(0.078)		
HH Used Dirty Cooking Fuel (Last 3 Months)	−0.049**	0.760	−0.036	0.755	1500.000
	(0.020)		(0.023)		
HH Used Dirty Cooking Fuel (Dumsor)	−0.028	0.802	0.002	0.796	963.000
	(0.029)		(0.033)		
Column Type	Coef.	Ctrl. Mean	Coef.	Ctrl. Mean	
Fixed Effects	cluster_priority_0		cluster_priority 1		
SE Cluster	cluster_priority_0		cluster_priority_1		

Business Variables

We report our results for business-related power outcomes in Table12. We find some evidence that businesses in priority areas are less willing to pay for perfect reliability or half of the current outage, which may indicate businesses already subject to relatively high power quality at least compared to their counterparts on ordinary feeders, that their marginal benefit of additional electricity improvements is less. We note, however, that this result is only significant using our buffer-zone approach. Furthermore, we find some evidence that businesses in priority areas are more likely to use alternate energy sources both in the current period and were more likely to use them during the Dumsor period – but these results are also not consistently significant across both specifications. One argument for why priority households would use more alternate energy during both the current and the Dumsor period is that they may be more reliant on energy services since they live in a place with higher power quality – which implies that the marginal benefit of any alternate energy use may be higher. As before, a key indicator for this would be an increase in the value of appliances held by business–which does not show up in these results. Yet, the previous argument presented in our analysis of the household outcomes in Table10applies–that having more or higher value appliance holdings does not necessary imply that their willing-to-pay for electricity is higher.

Table 12: Business Power Variables – Primary Outcomes

	Priority (Base)		Priority 2 (50M)		Obs.
	(1)	(2)	(3)	(4)	(5)
WTP Perfect Reliability (GHS/Month)	0.737	16.754	−2.880**	17.518	1500.000
	(1.969)		(1.376)		
WTP Half of Current Outage (GHS/Month)	−0.692	6.328	−1.569*	6.465	1457.000
	(1.095)		(0.839)		
WTP for Generator (GHS)	240.774	2848.792	126.492	2877.965	1411.000
	(204.364)		(245.485)		
WTP for 50 GHS Electricity Credit	3.137	61.950	3.285	61.928	1500.000
	(2.501)		(2.442)		
Value of Protective Investments	6.677	16.814	3.403	17.372	1500.000
	(4.740)		(5.654)		
Value of Protective Investment (June 2015)	0.428	5.237	−2.367	5.734	1500.000
	(1.666)		(1.456)		
Amount Paid for Multi-phase System in Dumsor (GHS)	0.428	5.237	−2.367	5.734	1500.000
	(1.666)		(1.456)		
Value of Appliances (GHS)	−84.304	1187.579	−66.580	1162.890	1500.000
	(73.912)		(74.071)		
Count of Appliances	0.322*	4.672	0.169	4.698	1500.000
	(0.174)		(0.144)		
Daily TV Use (Hours)	−0.306	3.821	−0.139	3.751	1500.000
	(0.250)		(0.468)		
Daily Cooling Appliance Use (Hours)	0.620	8.690	−0.157	8.883	1500.000
	(0.654)		(0.434)		
Daily Lightbulb Use (Hours)	−0.558	7.156	−0.707***	7.178	1488.000
	(0.375)		(0.257)		
Alternate Energy (0/1)	0.032***	0.056	0.014	0.061	1500.000
	(0.012)		(0.014)		
Alternate Energy (Dumsor) (0/1)	0.067**	0.164	0.037	0.173	675.000
	(0.033)		(0.037)		
Value of Convenience Appliances	−9.541	360.352	−44.477	364.471	1500.000
	(33.881)		(41.189)		
Column Type	Coef.	Ctrl. Mean	Coef.	Ctrl. Mean	
Fixed Effects	cluster_priority_0		cluster_priority 1		
SE Cluster	cluster_priority_0		cluster_priority_1		

In Table13, we report the impacts on key business indicators–such as profit, revenue, expenses and credit–in addition to the responsiveness to electricity reliability and other adaptive behaviors. We find no significant difference between the profits, revenue and expenses of businesses in priority and ordinary areas. We do, however, find that businesses in priority areas have significantly less outstanding debt–a nearly 20% wedge between businesses in priority areas and their counterparts in ordinary areas. However, priority businesses are less likely to have applied for credit in the past 12 months. Suggesting this result may not be due to higher repayment rates for pre-existing loans by priority businesses but instead taking out fewer loans or having less access to credit. With respect to power reliability, we find that businesses in priority areas are more likely to have both temporary and permanent responses to changes in power reliability. As be- fore, this may be due to the fact that since these business are located in areas with relatively good power quality, they may be more reliant on energy to run their business, and thus more likely to respond to changes in reliability. We also observe that these households usually operated their business for about 30 minutes more than their ordinary counterparts during Dumsor–a roughly 5% increase.

Table 13: Business Outcome Variables – Primary Outcomes

	Priority (Base)		Priority 2 (50M)		Obs.
	(1)	(2)	(3)	(4)	(5)
Total Profit (Last Month - GHS)	34.609 (52.733)	604.333	−10.402 (76.308)	622.293	1363.000
Total Revenue (Last Month - GHS)	−87.064 (291.771)	2552.140	−433.914 (349.755)	2665.423	1409.000
Total Expense (Last Month - GHS)	−92.009 (402.635)	1975.824	−318.245 (476.787)	2058.147	1499.000
Total Employees	0.094 (0.108)	1.999	−0.121 (0.088)	2.048	1500.000
Full-Time Employee Share	−0.001 (0.014)	0.916	0.010 (0.013)	0.915	1494.000
Total Employees (Dumsor)	0.064 (0.257)	2.319	−0.301 (0.198)	2.387	675.000
Usual Open Hours	0.271 (0.199)	12.133	0.139 (0.179)	12.158	1500.000
Usual Open Hours (Dumsor)	0.585*** (0.185)	11.775	0.598*** (0.152)	11.788	675.000
Open During Non-Daylight Hours	0.046 (0.037)	0.763	0.017 (0.036)	0.767	1500.000
Open During Non-Daylight Hours (Dumsor)	0.040 (0.026)	0.865	0.051** (0.024)	0.863	1500.000
Temp. Response to Reliability (Index)	0.189** (0.079)	−0.022	0.242*** (0.084)	−0.022	1500.000
Perm. Response to Reliability (Index)	0.151** (0.059)	−0.014	0.084 (0.067)	0.004	1500.000
Temp. Response to Reliability (Dumsor) (Index)	0.307** (0.125)	−0.045	0.350*** (0.122)	−0.043	675.000
Perm. Response to Reliability (Dumsor) (Index)	0.085 (0.108)	0.007	0.090 (0.139)	0.002	675.000
Business Challenge Index	0.202 (0.177)	−0.066	0.035 (0.221)	−0.041	1500.000
Revenue Difference with Perfect Reliability	49.040 (43.483)	219.076	33.961 (46.384)	232.038	1355.000
Total Outstanding Loans (GHS)	−115.107* (66.637)	491.926	−131.062** (56.266)	493.733	1500.000
Applied for Credit (Past 12 Months)	−0.072*** (0.026)	0.247	−0.055*** (0.021)	0.241	1500.000
Column Type	Coef.	Ctrl. Mean	Coef.	Ctrl. Mean	
Fixed Effects	cluster_priority_0		cluster_priority 1		
SE Cluster	cluster_priority_0		cluster_priority_1		

9 Discussion

We find some evidence that electricity reliability is correlated with certain economics outcomes – such as willingness-to-pay for electricity and household income. However, we note these results are not systematically significant and do not paint a very complete picture of the impacts of electricity reliability. Most of the non-significant results are imprecise–suggesting that we cannot rule out either large positive or negative impacts for most variables. In contrast, if many of our coefficients were not statistically significant from zero but possessed very tight 95% confidence intervals, we could say with more conviction that electricity reliability does not impact these variables.

As such, we decided to a1empt to understand if there are any additional considerations that are not included in this analysis that may bias our results either in terms of a1enuation or precision. For this – we run another set of diagnostic regressions using our data to test whether households who were assigned to priority actually experienced be1er power quality during Dumsor. For this, we lean on data that we asked of those included in the recall sample to recall their outage experience during Dumsor and compare this to the data in the situational reports.

We highlight this analysis in Table14, where we estimate the impact of priority assignment on the reported hours of outage via the situational reports and the recall data asked of our respondents. The first four columns pertain to our first assignment mechanism using the nearest lines and the last four columns reflect analysis using the buffer zone approach. In both cases, we un- cover that the difference in outages between priority and ordinary households and businesses is about 200 hours, which is promising given the analysis in Figure4. However, once we conduct this same analysis using recalled outages, we obtain a result that is about one-tenth the size, and which is only significant once we control for EA-Group level fixed effects. If we accept this result at face value–obviating concerns about the validity or veracity of recall data more generally–this suggests that the experience outlined by the situational reports makes the difference in outage between our priority and ordinary feeders about 10 times more severe than it is in actuality. Obviously, if the situational reports overstate the difference in power availability across our treatment variable, than we may not expect to find benefits to electrification since the actual difference between priority and ordinary households was not that stark.

One obvious–and plausible–reason for this difference is that recall data is subject to significant bias. We are asking respondents to recall the situation nearly 5 or more years prior, and as such, we may expect them to incorrectly quantify the amount of outages. Nevertheless, finding that the difference in recalled outages is much smaller than that measured in the situational reports could derive from households who experienced low outages over-reporting recalled outages or households who experience high outages under-reporting–or a combination of both. However, we have no way to validate this hypothesis absent any recall data that we can compare against a known baseline value to test if respondents are able to properly recall their previous outage levels.

If we accept the recall data as correct–or at least give credence to the idea that the situational report data does not accurately reflect the actual situation on the ground–another plausible explanation is that additional infrastructure exists to more surgically control power supply at the sub-feeder level. For example, if a switch existed below the feeder that could cut off power to the residential areas of a priority feeder, but maintain supply to the piece of key infrastructure (i.e. a hospital) on that feeder. If this does exist, than even though we observe massive differences in feeder level outages, it could be that through the use of others means of isolation, the households connected to that hospital via the same feeder actually experienced a much higher level of outage. Our contacts at ECG validated that infrastructure like this does exist–which they call isolators–but they could not provide detailed data on their usage as they do with the situational reports. However, ECG did provide a list of isolators and their respective feeders to us, but none of the isolated matched up with the feeders included in our analysis. Nevertheless, this remains an open question at this point in our analysis and is something we plan to investigate thoroughly as we iterate on this analysis and prepare our research for publication.

While these results are unse1ling for our research, we want to use this opportunity to draw particular a1ention to these considerations to alert future researchers about the complication of conducting studies based on incomplete administrative data. Our results are noisy and imprecise – and it is difficult to tell if they are artefact of electricity reliability not leading to large socioeconomic impacts, or are simply an artefact of measurement error between feeder level outages and what is truly experienced on the ground. Disentangling this in the context of this study will involve further work, which we plan to conduct, however, we want to note that for future research, it is important to consider what measurements are required to accurately measure the impacts of electricity reliability.

In our case, we had what seems like a perfect natural experiment – and the outage data to match. However, even in this very data rich environment, we still have hurdles to overcome to validate our analysis. As such, if policy makers and researcher are interested in answering this question with precision and validity, it is important that we obtain access to accurate, reliable and high frequency outage data that we can easily a1ach to respondents or business. However, even with these data, we still need some level of exogenous variation in electricity reliability in order to obtain casual estimates of the impact of electricity reliability on socioeconomic outcomes. As such, we think it is worth while for these data collection efforts to exist outside of a single research project, but instead, be on-going so that any exogenous shock to electricity supply for a subset of otherwise comparable individuals can be validated and used to accurately study the impacts of electricity reliability.

Table 14: Priority Status and Dumsor Monthly Electricity Outage Hours

	Most Likely Feeder Priority Status				50M Buffer Zone Priority Status			
	Situational Reports		Recalled Outages		Situational Reports		Recalled Outages	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Priority (Most Likely Feeder)	−216.649***	−219.143***	3.926	−22.463**				
	(14.071)	(6.684)	(12.776)	(8.710)				
Priority (50M Buffer Zones)					−190.834***	−176.826***	2.140	−24.224***
					(16.868)	(10.627)	(13.205)	(8.031)
Control Group Mean	230.45	230.45	213.25	213.25	211.88	211.88	213.97	213.97
Observations	3013	3013	1310	1310	3013	3013	1310	1310
Number of EA Groups	26	26	26	26	26	26	26	26
EA Group Fixed Effects		Y		Y		Y		Y

10 Conclusions

In this annex, we report the results of our natural experiment measuring the socioeconomic impacts of electricity reliability for households and businesses in Ghana. We leverage exogeneous variation in the electricity supply to otherwise comparable households that is induced by the predetermined electricity network in Accra. Notably, we use the fact that some households are connected to feeder lines that service critical loads, and thus were prioritized for less load shedding during the Dumsor crisis between 2012 and 2016. The administrative ECG data on outages at the feeder level suggests that the difference in outages in substantial between priority and ordinary feeders–a difference of nearly 200 hours/month on average. We assign households to feeders of different categorizations using detailed geographic data on the grid infrastructure, and use the difference in electricity reliability induced by the feeder they happen to be connected to determine the casual impacts of improved electricity reliability.

Our results suggest that households subject to increased electricity supply have a greater willingness-to-pay for electricity credits, but do not measure the transformative changes in socioeconomic outcomes that we posit in our pre-analysis plan in terms of key socioeconomic outcomes such as income, employment, education and investment in appliances.

The results for business are similar – and do not suggest that electricity reliability led to any change in revenue, costs or profits. However, we do find that businesses in priority areas were open longer during the Dumsor crisis and are more likely to make temporary responses to reliability, which may suggest that they are more dependent on a reliable electricity supply to run their business. We note, however, that most of our firms are single-person firms and may not reflect the importance of electricity supply for larger firms with more employees.

Given the underwhelming results posed by our analysis, we do our best to untangle if these results are really indicative of reliability not leading to sizable changes in socioeconomic outcomes, or if there are other reasons. As noted in our discussion of the results, the recall data paint a very different picture than the ECG-reported outage data, which may lead to significant a1enuation bias in our results. The administrative ECG outage data suggest a nearly 200 hour/month difference in outages during the Dumsor period between priority and ordinary areas, whereas the recall data suggest an effect about one-tenth this size. As such, if the administrative ECG outage data do not reflect the reality of outages for households, than our analysis may be subject to bias. Furthermore, the inclusion of sub-feeder infrastructure that may control electricity more surgically may impact our results, as ECG verified that sub-feeder level isolators exist which may be used to retain power to a prioritized load center on a feeder while disconnecting non-prioritized loads. However, we obtained a list of these key pieces of infrastructure and their associated feeders, and found no overlap with the feeders included in our analysis.

The final results of our analysis are still pending validation and additional work to ensure the ECG situational report data accurately portray the reality on the ground for individual consumers. For future research, we note that ensuring access to high-quality, high-frequency data on electricity outages–which can accurately be matched to individual consumers–will ensure that researchers can leverage natural experiments–like the Dumsor crisis–to conduct casual analysis on the impacts of electricity reliability.

References

Abdullah, S. and Jeanty, P. W. (2011). Willingness to pay for renewable energy: Evidence from a contingent valuation survey in kenya. *Renewable and sustainable energy reviews*, 15(6):2974–2983.

Abeberese, A. B., Ackah, C. G., and Asuming, P. O. (2021). Productivity losses and firm responses to electricity shortages: Evidence from ghana. *Le World Bank Economic Review*, 35(1):1–18.

Alberini, A. and Cooper, J. (2000). *Applications of the contingent valuation method in developing countries: A survey*, volume 146. Food & Agriculture Org.

Allco1, H., Collard-Wexler, A., and O'Connell, S. D. (2016). How do electricity shortages affect industry? evidence from india. *American Economic Review*, 106(3):587–624.

Berkouwer, S. B., Biscaye, P. E., Hsu, E., Kim, O. W., Lee, K., Miguel, E., and Wolfram, C. (2021). Money or power? financial infrastructure and optimal policy.

Berkouwer, S. B., Biscaye, P. E., Puller, S., and Wolfram, C. D. (2022). Disbursing emergency relief through utilities: Evidence from ghana. *Journal of Development Economics*, page 102826.

Deutschmann, J. W., Postepska, A., and Sarr, L. (2021). Measuring willingness to pay for reliable electricity: Evidence from senegal. *World Development*, 138:105209.

Dzansi, J., Puller, S. L., Street, B., and Yebuah-Dwamena, B. (2018). The vicious circle of blackouts and revenue collection in developing economies: Evidence from ghana.

Fisher-Vanden, K., Mansur, E., and (Juliana), Wang, Q. (2015). Electricity shortages and firm productivity: Evidence from china's industrial firms. *Journal of Development Economics*, 114(C):172–188.

Hardy, M., Mbiti, I. M., Mccasland, J. L., and Salcher, I. (2019). The apprenticeship-to-work transition: experimental evidence from ghana. *World bank policy research working paper*, (8851).

Sievert, M. and Steinbuks, J. (2020). Willingness to pay for electricity access in extreme poverty: Evidence from sub-saharan africa. *World Development*, 128:104859.

The World Bank (2013). Enterprise surveys.

UN General Assembly (2016). Transforming our world: The 2030 agenda for sustainable development.

Annex B: Final Survey Instrument

GridWatch PF-LB
Paper Questionnaire_

Annex C: MCC Comments & Evaluator Responses

Reviewer Institution/Role (include sector reference)	Page Number	Comment	Evaluator Responses
MCC M&E	vi	Please see suggested minor re-org of text and heading, and please also add a brief description of the evaluation questions (without listing them out in sequence) prior to the disucssion of data sources - for instance, "the evaluation questions focus on the impact of the infrastructure investments on… (etc.)"	Done
EPG	vi	The LB intervention involves injecting new transformers in the LV network, "bifurcating" existing LV lines. It also included uprating of existing transformers, conductors and underground cables and replacement of existing rotten poles and damaged accessories. During the project implementation, we also added installation of stay insulators on structures where there were missing.	Text was deleted and reorganized by MCC in the tracked changes version.

EPG	vi	According to the program logic for the LB intervention, the expected output of the LB intervention is to reduce the length of LV circuits–the distance between transformers–to improve the quality of service. The targeted immediate short-term outcome of the LB intervention is to improve power reliability and quality. The theorized long-term outcomes from the intervention include improved economic outcomes for customers, realized by reduced spending on dealing with poor reliability and on alternative energy sources, increased electricity consumption, improved usage of electric appliances, reduced work disruptions, and increased revenues and profits for businesses. Also reduced electricity related hazards.	Changed
MCC M&E	vii	"The surveys collect detailed data on customers' energy usage, including... ownership and usage of electricity protection devices (including generators), use of alternative energy sources,..." Just noting that generators would be considered more of an alternative energy source as opposed to a protection device.	Changed
MCC M&E	vii	The first paragraph on p. vii states twice that data are being used to confirm balance at baseline (both device and survey data), and then the third paragraph re-states this again regarding the surveys. Suggest deleting reference to balance testing in the first paragraph and just leaving it in the 3rd.	Changed
MCC M&E	vii	"The business survey sample targeted small and medium-sized businesses with 30 or fewer employees..." Does this mean to really say that small/medium businesses were specifically targeted for participation in the survey, i.e. based on screening criteria? Or just that small/medium businesses were strongly represented in the sample due to the location of LB / survey	We targeted small and medium-sized businesses specifically but our sample is strongly skewed toward very small businesses (fewer than 5 employees).

		sites? Please clarify the wording if it's the latter.	
EPG	vii	The surveys collect detailed data on customers' energy usage, including electricity spending, appliance ownership and usage, ownership and usage of electricity protection devices (including generators) , use of alternative energy sources, and impacts of reliability issues. Generators are not electricity protection devices. Probably meant " ..... usage of electricity protection devices and generators	Changed
MCC M&E	viii	Please present some basic data alluded to in the summary of Evaluation Question 1 -- e.g. mean daily outage minutes, share of devices reporting bad voltage, and/or average outage duration over past 30 days. Be sure to present any relevant baseline data for each evaluation question, and if the evaluation question itself is not answerable at baseline, say so explicitly (but still present applicable baseline data or findings, key comparisons, observatios).	This exists in the main body text, we've added some details in the Exec Summary now.
EPG	ix	Impacts of Poor Reliability I suggest that you create two subsection; - Impacts on Households - Impacts on businesses	It is separated out by Households and Businesses in the main report.
EPG	ix	2. Some businesses can switch tools or activities in response to outages, but stopping work is the most common temporary response to power outages. This is not clear. Please re-phrase. Do you mean switch from electric tools to manual tools?	Changed

EPG	ix	4. Households use electricity in a variety of ways, making it challenging to measure how unreliable electricity affects them outside of their energy use and spending. Loss of perishable food is one important challenge, reported by 27% households. Electricity outages do not appear to create difficulties for cooking, as electricity is not a primary cooking fuel for most households. I suggest that to give a better picture, you present the top three challenges for Households and not just one.	It is mentioned in the main body text.
MCC M&E	x	"The median respondent is willing to pay around 15% of their monthly electricity spending to ensure perfect reliability, though some respondents indicate being willing to pay much more. Around one-third of households and businesses are not willing to pay anything for perfectly reliable electricity." Presumably this is interpreted as respondents being willing to pay (or not) ***more*** for perfect reliability -- i.e. one-third of HH / businesses are not willing to pay anything ***more*** fore perfect reliability.	This interpretation is correct. WTP for perfect reliability is above and beyond current usage-based spending.
EPG	x	Willingness to Pay for Improved Reliability Please separate the narrative as; Households Businesses For each mentioning willingness to pay for Grid improvement and willingness to pay for generator as a means to improve reliability of supply. On a related note, was an Ability to Pay assessment done?	Added at the bottom of page 61. The reliability WTP amounts are very similar for HHs and businesses: USD 3.2 per month for HHs and 3.0 per month for businesses. Exec summary for generator WTP already separated out. We do not ask about or assess ability to pay. Respondents may be overstating their WTP since it is all hypothetical.

EPG	x	1. We elicited respondents' willingness to pay (WTP) for different scenarios of improved electricity reliability and for a generator . The median respondent is willing to pay around 15% of their monthly electricity spending to ensure perfect reliability, though some respondents indicate being willing to pay much more. Its not clear what they would be paying for. Please clarify. Is it Willingness to Pay a higher tarrif, WTP for new equipment, etc?	Changed
EPG	x	*Households and businesses may invest more in power-consuming technology as electricity reliability improves and their ability to benefit from such investments increases, if they believe that the reliability improvements are large and likely to last. Such changes may not be detectable by the end of the exposure period for the line bifurcation construction treatment, but questions about appliance ownership and purchase plans can provide insight into consumer perceptions of reliability and awareness of any improvements.* I suggest you instead state a percentage of respondents that would invest in more power consuming equipment as electricity reliability improves.	We have a graph in the main report showing the percentage.
MCC M&E	xii	Suggest changing final heading to 'Assessment of program logic risks' and focus the conclusion of the Exec Summary on any of the most salient risks to the logic that may be suggested by baseline findings.	Changed
MCC M&E	xii	"Businesses in particular could benefit from fewer work disruptions, ***though benefits may be small for the large share of businesses that do not appear to rely on electricity for their operations***." The Executive Summary doesn't seem to call out any particular finding where a large share of businesses do not realy on electricity for operations -- where is this? If this is shown	Rephrased to accurately reflect the conslusion we were trying to make.

		to be true, this would be important to highlight but it is not mentioned in any of the summarized findings that I can see.	
MCC M&E	8	I suggest a slight re-ordering of the sections under Part 2: Overall section heading should be 'Evaluation Design,' with a brief mention of the Evaluation type (impact), followed by the Evaluation Questions, then methodology.	Changed
MCC M&E	11	The report observes that "The DD econometric identification assumption relies on two testable requirements" - parallel trends, and site selection criteria not correlating with outcomes of interest. Is it also worth mentioning that the identification also relies on limited network effects leading to spillover of reliability benefits into control areas?	Added to the bottom of page 12
EPG	Page 13	Technical data on power reliability and quality is collected using the GridWatch suite of technologies, which in Accra will consist of several hundred deployed PowerWatch devices, linked and analyzed through cloud computing software. PowerWatch devices have been deployed in line bifurcation sites since June 2018. This statement partly suggests that the equipment was installed in 2018 but the other part suggests that it is to be installed in future. Which is it?	Changed
MCC M&E	14	The report notes here that "we are working with ECG to obtain data on outages at the feeder level for study areas to analyze general outage trends…" Can this clarify that if obtained, this analysis will be included in the endline report? It may be worth discussing whether to add an evaluation question to examine/compare the quality/completeness of ECG outage	Noted for further discussion.

		data to Gridwatch data, a key capability enabled by the GW platform.	
MCC M&E	16	Not a deal breaker and perhaps just something to consider for the endline report rather than a further revision to this report, but: in each of the data tables throughout the report (for instance Table 2), the quartiles of the distribution of each variable aren't really necessary. Mean and SD are fine, and perhaps just including the range (min-max) would be perfectly approprpiate. Also, one added consideration for presentation of binary variables: it may be more straightforward to most readers (esp. those lacking a heavy stats background) to just present these as percentages (using % to denote the unit) rather than as a decimal. Then you wouldn't have to include the text '(=1)' for each variable - something those without a stats background might not understand.	Noted and will keep in mind for endline report.
MCC M&E	24	Please check/confirm the notes under Table 6, which states that '***' is used to denote p<0.01; This seems to conflict with the single ‘*’ which is supposed to denote p<0.01.	Noted and corrected everywhere in the report.

MCC M&E	28-29	Figure 8 and supporting text on pre-post construction data on voltage: Based on the graph in Fig. 8, is it accurate to say that control sites appear to exhibit quite pronounced network effects from the LB investment? The text notes that treatment sites "had better voltage quality than control sites" from April-Aug 2021, which is depicted in Fig 8 -- however, control sites clearly show at least an initial pattern of improved voltage profiles, with a magnitude of change between pre/post that appears quite large in comparison to the ***difference*** between treatment/control. If this is an accurate assessment, it may be useful to talk about what implications there may be for the identification strategy.	The pattern of the control group does not appear very different from the existing annual cycle. Added this at the bottom of 3.2.1
EPG	Page 40	It would have been helpful to create a summary at the end of the detailed discussion that presents the parameters used to answer the question of the current status. That will make it easier to revert to and compare at endline.	
MCC M&E	57	The heading for Fig. 29 makes this more clear, but I'm understanding the text here in the same way – most respondents ***among households that use electricity for cooking*** – i.e. among the 6.7% that ***do*** use electricity for cooking, 91% of ***those*** respondents turn to other fuels.	Changed

MCC M&E	73	"having all male employees is associated with GHS 580 (USD 88) more profits than having all female employees, holding all else constant. These results highlight differences in the types of business activities that women and men engage in…" Very fascinating - I can't recall if the report indicated prior, but can this state (or re-state) what types of business activities are most common for all male vs. all female businesses? I'd even be curious if there is a significant difference in size (# of employees) between all male / all female businesses.	This isn't in the report previously and we were stating as just showing evidence that there must be differences. Here are some stats. All-male businesses have 1.95 employees on average and 22.7% are engaged in retail activities, compared to 1.51 employees and 49.5% engaged in retail for all-female businesses. Both have 2.8 appliance types and are open for around 12 hours per day on average.
MCC M&E	74	See questions / comments on Table 15 (within the document). Some of the indicators / results presented are unclear, but uncertain whether this is a formatting issue.	Formatting changed.
MCC M&E	87	Risks to program logic and evaluation design -- it would be useful to add a brief discussion of risks to the evaluation due to network effects leading to spillover of benefits into control sites, if the team agrees that this remains a risk (and if initial voltage quality data suggest network effects are potentially occurring). Similarly, consider whether to also include a brief discussion on how the evaluation design may (or may not) be able to isolate the LVB reliability benefits from other upstream investments - e.g. BSPs and primary substations; for instance whether the continuous / real-time data will enable temporal analysis of reliability changes (mapped to the timeline for completion of BSPs/PSS).	Such investments will invest in control and treatment sites simultaneously, thus this will not affect our ability to measure differences between control and treatment sites that result from the LVB in treatment sites.

MCC M&E	92	"A benefit of the evaluation design is that customers do not need to perceive any reliability improvements in order to experience long-term benefits." This is actually a benefit of the LB intervention itself.	Changed
MCC M&E	90	"Businesses could benefit from fewer work disruptions, though benefits may be small for businesses that do not rely on electricity for their operations. Those that do, such as clothing manufacture and repair businesses, could see increased revenues and profits." This will be an especially interesting finding to explore in the endline analysis, as an understanding of relative impacts on small businesses is a key area of learning; larger businesses tend to cope more effectively with outages due to more widespread use of backup generators.	Noted for endline report.